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The impact of government-supported participative loans on the growth of entrepreneurial ventures

Fabio Bertoni[a,*], Jose Martí[b], Carmelo Reverte[c]

[a] Emlyon Business School, France
[b] Universidad Complutense de Madrid, Spain
[c] Technical University of Cartagena, Spain

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ABSTRACT

We study the employment and sales growth of entrepreneurial ventures that have received a government-sponsored participative loan (PL), a hybrid form of financing between debt and equity. We use propensity-score matching (PSM) and instrumental variable analysis (2SLS) to study a sample of 512 entrepreneurial ventures that received a PL from a Spanish government agency between 2005 and 2011. We find evidence that PLs significantly boosted their beneficiaries' employment and sales. In the two years following loan issuance, a 1-million-Euro PL generated an increase in average employment of between 12.1 (PSM) and 14.7 (2SLS) units and an increase in sales of between 1.09 and 1.97 million Euro relative to the average for the two years prior to loan issuance. The effect is larger for high-tech, young and small entrepreneurial ventures and for those that received a PL during the global financial crisis. The effect on growth is significant and stable, and PLs increase their beneficiaries' annual growth by 10.6% for employment and by 18.0% for sales. We do not find evidence of industry or regional spillovers, nor do we find differences in the probability of survival of PL beneficiaries after we control for their characteristics.

1. Introduction

In this paper, we provide evidence regarding the extent to which young entrepreneurial firms benefit from a relatively recent form of government support: participative loans (PLs). Governments have provided support to young entrepreneurial firms essentially for two reasons. First, young entrepreneurial firms are likely to be the fast-growing firms that contribute most of the innovation and job creation that comes from small and medium enterprises (SMEs). Second, these key companies are those that face the most significant financing hurdles (Freel, 2007). Young entrepreneurial companies experience more difficulties in accessing external financing from financial institutions than do large and more established firms (Beck et al., 2008; Freel, 2007; Hutton and Lee, 2012; Mina et al., 2013; Schneider and Veugelers, 2010). Their access to external finance is hampered by numerous structural factors, including high uncertainty (Coad and Rao, 2008; Hall, 2002), information asymmetries (Carpenter and Petersen, 2002a; O'Sullivan, 2006) and a lack of internal financing and collateral (Berger and Udell, 1990; Binks et al., 1992; Carpenter and Petersen, 2002b). Access to external equity is hampered by high issuing costs and the scarcity of venture capital (VC), which is accessible to only a very limited percentage of firms (Sahlman, 1990). These concerns have been exacerbated during the global financial crisis (GFC), which caused a credit crunch that contributed to a significant slowdown of entrepreneurial activity (Bartz and Winkler, 2016) and economic recovery (Cowling et al., 2012; Filippetti and Archibugi, 2011). The GFC has accentuated the structural factors hindering access to finance to firms that are innovative (Lee et al., 2015) and have a high-risk credit rating (Cowling et al., 2016).

Concerned about the funding gap that hinders young entrepreneurial ventures from exploiting growth opportunities, governments have created schemes to increase the availability of long-term financing to entrepreneurial ventures (Colombo et al., 2016; Cumming et al., 2009). These schemes include: subsidies to investment and research and development (R&D), subsidized loans and loan guarantees, and government-supported equity through VC. There is vast empirical evidence on the effectiveness of each of these policy instruments. The debate about R&D subsidies focuses on their additionality with respect to private investments (e.g., see Czarnitzki and Delanote, 2015; Zúñiga-Vicente et al., 2014). Most – albeit not all – studies on the effectiveness of subsidized loans and loan guarantees find that these schemes have a positive effect on beneficiaries' growth and performance (e.g., Brown

* Corresponding author.
E-mail address: bertoni@em-lyon.com (F. Bertoni).

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and Earle, 2017; Kang and Heshmati, 2008; Meager et al., 2003; Oh et al., 2009; Riding and Haines, 2001), but not necessarily on their ability to transform R&D into innovation (Cowling, 2016). The results for government-sponsored VC funds show less encouraging results: they indicate that the effect is negligible (or even negative), with the possible exception of co-investments with private VC funds (Alperovych et al., 2015; Bertoni and Tykvová, 2015; Cumming et al., 2017; Grilli and Murtinu, 2014).

In an effort to extend non-bank sources of financing to entrepreneurial ventures (as suggested by Fraser et al., 2015, among others), policymakers have directed their attention to hybrid instruments that combine debt and equity features (Infelise, 2014; OECD, 2015). However, empirical evidence of the effectiveness of these hybrid instruments is limited. In this work, we aim to fill this gap. Specifically, we study the effectiveness of PLs granted by government agencies to foster the growth of young entrepreneurial ventures. Similar to straight loans, PLs have a predetermined maturity and interest payments, but similar to equity, payments are contingent on the profits of the beneficiary firm. In this way, PLs are an interesting form of entrepreneurial finance: the borrower does not face internal capital dilution or a high cost of funds in the initial years, and the institution granting the PL obtains additional income from successful firms without bearing the cost of managing and selling a portfolio of equity stakes.

We focus on PLs granted to entrepreneurial ventures by *Empresa Nacional de Innovación* (ENISA), a government agency funded by the Spanish Ministry of Economy, Industry and Competitiveness. Spain is a precursor in the use of PLs (Infelise, 2014), which are also used in France (French ISODEV agency) and Italy (Agliata et al., 2014). To be eligible to obtain a PL from ENISA, an applicant must be a small or medium enterprise (SME, according to the official EU definition provided in the Commission Recommendation of 6 May 2003) and must not operate in real estate or financial services. Applicants must undergo a meticulous screening process, and ENISA rejects approximately half of the proposals it receives (Martí and Quas, 2018).

Our sample comprises 512 firms established after 2003 that received a PL from ENISA between 2005 and 2011. We analyze the employment and sales growth of these firms and follow their performance until 2014. In our main analysis, we estimate the employment creation and sales increase per million Euros granted in a PL, along the lines of Brown and Earle (2017). The effect is larger for high-tech, young and small entrepreneurial ventures and for those that received a PL during the global financial crisis. Using the methodology of Grilli and Murtinu (2014), we also estimate the increase in the firm's employment and sales growth rate after PL issuance. Finally, we provide preliminary evidence on the survival of PL beneficiaries and the presence of regional and industry spillovers due to PLs.

This work contributes to the evidence on the impact of policy measures undertaken by public authorities to fill entrepreneurial ventures' funding gap (Hyytinen and Toivanen, 2005). More precisely, we extend the evidence on the effectiveness of several policy instruments, such as R&D subsidies, loan guarantee programs, subsidized loans, and government-supported VC, to the usefulness of hybrid instruments in boosting entrepreneurial venture growth.

The rest of the paper is structured as follows. In Section 2, we present the theoretical background of our work. In Section 3, we present the data and the methodology used to test our hypotheses. We describe our results in Section 4 and provide additional evidence in Section 5. Finally, in Section 6, we discuss our findings and conclude our work.

2. Theoretical background

2.1. Debt and equity schemes for entrepreneurial ventures and their effects on growth

The existence of frictions such as information asymmetry, agency costs and transaction costs (Fama and Jensen, 1983; Jensen and Meckling, 1976; Myers and Majluf, 1984) affects a firm's capacity to access external financing in complex ways, which can require different types of government intervention. Stiglitz and Weiss (1981) provide theoretical support to the existence of gaps in the debt markets as a result of both adverse selection and moral hazard problems. Under different assumptions about the distribution of project outcomes, de Meza and Webb (1987) show that overinvestment in risky projects may occur in equilibrium. Depending on the underlying assumptions of the model, different types of government intervention are justified, including loan subsidies and guarantees, the taxation of investment, and R&D subsidies (Boadway and Keen, 2006; Innes, 1991; Takalo and Tanayama, 2009).

The empirical evidence on entrepreneurial ventures indicates that the type of information asymmetry they face results in a lack of financing that hinders their ability to grow (Gompers, 1995; Michaelas et al., 1999), especially in the case of innovative and fast-growing firms (Binks et al., 1992; Binks and Ennew, 1996) and during a period of crisis (Lee et al., 2015).

Government authorities are deeply concerned by this issue. In recent decades, they have implemented a wide variety of schemes to offer entrepreneurial ventures access to long-term financing. The extant literature provides mixed evidence on the effects of many of these policy measures, which include R&D/investment subsidies, subsidized loans, loan guarantee programs and government-backed VC. We will briefly review the literature on each of these four types of schemes in the remainder of this section.

The academic debate – which is summarized in Czarnitzki and Delanote (2015) and Zúñiga-Vicente et al. (2014) – does not reach a consensus about the additionality of R&D/investment subsidies. In a recent meta-analysis, Dimos and Pugh (2016) reject the crowding out of private investment by R&D subsidies but reveal no evidence on a substantial additionality, which is also found in other meta-analyses reported by D'Andria et al. (2018). In the same vein, Decramer and Vanormelingen (2016) report a positive effect of these subsidies on employment but highlight that it is not large enough to justify the cost of the scheme. Similarly, other works find a positive effect on employment but a negative (Karhunen and Huovari, 2015) or negligible (Cerqua and Pellegrini, 2014) effect on productivity growth. With respect to the cost per job created, the average amounts reported in some works range between 60,000–70,000 Euros (Cerqua and Pellegrini, 2014; Koski and Pajarinen, 2013), whereas in others, the estimated amount could double that amount and even reach the half-million threshold (Decramer and Vanormelingen, 2016).

Turning to subsidized loans and loan guarantee schemes, Gale (1991) provides important results on how credit subsidies affect the economy. Dinh et al. (2013) show that a program of subsidized interest rate loans had a remarkable effect on the economy during the financial crisis. However, the authors also recognize that this type of program should be temporary and closely monitored. Koski and Pajarinen (2013) find that business subsidies, which include both subsidized loans and loan guarantees, may induce high growth in startups but are not effective in firms that were already considered high-growth firms.

There is abundant evidence on loan guarantee schemes. Riding and Haines (2001) and Chandler (2012) find that credit guarantee programs led to positive job creation in Canada. Using firm-level data on Korean credit guarantee programs, Kang and Heshmati (2008) and Oh et al. (2009) examine the determinants of guarantee use and the ex post performance of loan guarantee beneficiaries. Although the two studies employ different empirical approaches, they both find that the use of credit guarantees positively affects sales growth and reduces firms' failure rate. Based on data from the US Small Business Administration (SBA) loan guarantee program, Brash and Gallagher (2008) find that recipient firms experienced an increase in sales and employment after receiving the loan. Brown and Earle (2017) further analyze linked databases on all SBA loans and lenders and all US employers to estimate the effects of financial access on employment growth. Using propensity-score matching and instrumental variables, they find that each million USD in loans committed led to an increase of 3 to 3.5 jobs. They also argue that SBA loans did not simply replace conventional loans: recipients were genuinely credit-constrained prior to receiving these loans and the use of these loans led these firms to grow more than they would have grown otherwise. Asdrubali and Signore (2015) examine the final beneficiary-level economic impact of the SME Guarantee Facility program from the EU Multiannual Program for the enterprise and entrepreneurship (MAP) framework in Central, Eastern and South-Eastern European (CESEE) countries for the 2005–2012 period. Using propensity scores and difference-in-differences estimations, they find that the EU SME Guarantee Facility in the CESEE region had a significantly positive effect on employment on average.

In contrast to these studies, de Meza (2002) argues that there is a surplus of funds channeled to over-optimistic low-quality borrowers. In this regard, Meager et al. (2003) do not find a significant effect of UK low-interest start-up loans through the Prince's Trust on growth.

As a result, depending on the work analyzed, the estimated cost per job created could range between infinite (Meager et al., 2003) and only 6,000 Euro in Canada (Chandler, 2012), with the most recent reference in the US being approximately 25,000 USD (Brown and Earle, 2017).

Finally, the equity-based scheme type supporting entrepreneurial companies that has received the most attention in the academic literature is governmental VC, which has been widely used in Europe to promote the development of local VC markets (Leleux and Surlemont, 2003). Policymakers' interest in government-backed VC schemes derives from the effectiveness of private VC funds in supporting their portfolio companies in terms of R&D productivity (Kortum and Lerner, 2000), time-to-market (Hellmann and Puri, 2000), and productivity (Chemmanur et al., 2011; Croce et al., 2013; Croce and Martí, 2016). The extant literature also highlights the positive effect of private VC funding on investments (Bertoni et al., 2013) – a fundamental variable to explain growth – and on the reduction in the sensitivity of investments to internal cash flows (Balboa et al., 2017; Bertoni et al., 2013, 2010; Engel and Stiebale, 2014). These findings are consistent with the results of papers supporting the idea that VC financing leads to significant growth among investee firms (Alemany and Martí, 2005; Engel and Keilbach, 2007; Grilli and Murtinu, 2014). Government authorities have attempted to use VC as a tool to foster growth in specific regions and/or industries. The existing evidence, however, does not indicate a significant effect of governmental VC. Alperovych et al. (2015) find a negative effect of governmental VC on the efficiency of investee firms, whereas Bertoni and Tykvová (2015) do not find a significant effect of governmental VC on invention and innovation unless the investment is combined with funding from private VC investors. Focusing on firm growth, Grilli and Murtinu (2014) show that whereas independent VC funds accelerate sales and employment growth, this effect does not occur for firms financed by governmental VC funds except when this financing is combined with funding from private VC investors.

In summary, while evidence supports an overall positive effect of direct subsidies, subsidized loans and loan guarantees on firm growth, there is also a discussion regarding the efficiency of those policy measures from the perspective of government spending allocation. However, the evidence shows no significant positive effect of governmental VC – with the possible exception of syndicated deals – on growth and innovation. Government authorities have sought new, more effective policy instruments to boost growth (Infelise, 2014; OECD, 2015). One of these new policy instruments is PLs, which we discuss in the next section.

2.2. Government-sponsored participative loans: characteristics and effect on growth

PLs are hybrid instruments that feature characteristics of both loans and common stock. Similar to ordinary loans, PLs have regular interest payments that are based in part on a reference rate (e.g., Euribor) plus a spread. However, a second component of these interest payments is contingent on performance. This component is based on the company's profits in the relevant year and is usually capped. Both components are treated as tax-deductible interest expenses. Another element of PLs that makes them similar to equity is that they are deeply subordinated (ranking only above common equity) and are 'basketed' as 100% equity for financial analysis. Some institutions that grant PLs ask existing shareholders to match the PL with a capital increase.

These characteristics make PLs an attractive policy instrument to channel finance to entrepreneurial ventures. On the one hand, PLs give firms more flexibility than ordinary loans by providing a pattern of affordable interest payments before the borrower reaches the break-even point. This feature is potentially beneficial for entrepreneurial ventures at the startup or early development phase. On the other hand, the government's involvement does not entail equity capital dilution for the entrepreneurial ventures' shareholders. Furthermore, PLs do not require a specialized management structure to manage divestments (as required in the case of governmental VC) because, similar to ordinary loans, PLs have a predetermined maturity.

Similar to the case for R&D subsidies (Meuleman and De Maeseneire, 2012), government authorities gain substantial expertise in analyzing young entrepreneurial ventures' investment plans. The advantage in the screening process is derived from the centralization of a large number of applications, which allows government agencies to develop the skills needed to conduct independent and technically sophisticated valuations. Moreover, since the return on investment in PLs includes a share of the borrower's profits, it is in the lender's interest to be extremely selective in awarding PLs. Furthermore, PLs may reduce potential moral-hazard problems if the government agency requires the applicant firm to complete a capital increase to obtain the PL. This capital increase contributes to aligning the interests of shareholders and lenders. As a result, entrepreneurial ventures receiving PLs not only obtain long-term financing but are also essentially 'certified' to banks, which improves their access to additional long-term financing to fuel growth (Martí and Quas, 2018).

As funds are allocated to young entrepreneurial ventures, which are deeply financially constrained (Berger and Udell, 1998; Brav, 2009), the external financing obtained will help reduce investments' dependency on internal sources of finance (Carpenter and Petersen, 2002b). Thus, we expect that government-supported PLs will have a positive effect on beneficiary firms.

Since the universe of entrepreneurial ventures that can receive PLs from government agencies is large and diverse, the initial funding provided could be more beneficial for entrepreneurial ventures that are more strongly affected by information asymmetries. In particular, we argue that young and small entrepreneurial ventures and those related to high-technology industries are the most affected by information asymmetry problems.

Recently established firms demonstrate high uncertainty levels related to both the product development and the commercialization phases (e.g., Sørensen and Stuart, 2000). The provision of long-term funding via government-supported PLs at this stage allows newly born firms to initiate operations and begin building a track record that banks require to supply long-term financing.

Another important determinant of information asymmetry is firm size. The costs of information collection are high for small businesses (Binks and Ennew, 1996), most of which are unable to provide audited financial statements (Bernanke et al., 1996). In addition, the value of these firms' assets also limits the use of these assets as collateral (Binks et al., 1992). In this context, receiving a PL from a government agency may enable small businesses to obtain the long-term funding that is necessary to carry out future investments. Furthermore, the certification effect, which leads to easier access to banks, is more pronounced in smaller firms than in larger ones (Martí and Quas, 2018).

For high-technology firms, opacity is related to their reluctance to share information due to appropriability concerns (Teece, 1986). In addition, commercial banks are not prepared to evaluate technically sophisticated products (Lerner, 2002), and the use of collateral to reduce adverse selection is limited because these firms' assets are typically intangible (Carpenter and Petersen, 2002a). The certification effect of government-backed PLs, which grants easier access to banks, is also more pronounced for high-tech companies (Martí and Quas, 2018).

Finally, the empirical evidence suggests that the GFC has negatively affected entrepreneurial activity (Bartz and Winkler, 2016) and has amplified the structural factors that hinder access to finance to innovative firms (Lee et al., 2015; North et al., 2013), often causing the interruption of innovative activities (Paunov, 2012). Young entrepreneurial ventures are also likely to have a high-risk credit rating, which is a characteristic that amplified financial hardship during the GFC (Cowling et al., 2016).

In summary, we can expect that government-supported PLs will have a disproportionately beneficial effect on younger, smaller and high-technology firms, and on firms that obtained a PL during the GFC.

3. Data and methodology

3.1. Research setting

ENISA is an independent agency funded by the Ministry of Economy, Industry and Competitiveness. It was established in 1982 to provide equity financing to high-technology firms. As the Spanish VC market matured by the second half of the 1990s and more private VC players entered the market, ENISA gradually switched from investing in equity to granting PLs. In this way, ENISA opted to complement (rather than to compete with) private venture capitalists. With this approach, ENISA aimed to provide long-term funding to a broader universe of high-technology, high-growth entrepreneurial ventures. Because PLs are loan contracts (not shares), they do not require a formal valuation of the recipient firms equity value. Moreover, since PLs have a predetermined maturity, as ordinary loans do, it would not have to devote attention to divestments.

Since ENISA must prove its effectiveness to obtain funding from the government, its approach is different from that of a pure public-spending entity. The allocation of PLs follows a competitive process. All applicants must provide a business plan that includes a description of the venture, the background of the founders, a description of the business model, a justification of the destination of the amount required to ENISA, and cash-flow projections. Part of this information is submitted through an online platform.

The evaluation process usually lasts from two to three months. Applicants' rate of success in obtaining funding is approximately 50% (Martí and Quas, 2018). This success rate seems low when compared for instance to the 65%–80% reported by Cowling et al. (2012) for the proportion of businesses securing external financing between Dec-2008 and Feb-2010. The reasons for this low acceptance rate include the following. First, the information requested is huge and incomplete applications are rejected. After the preliminary analysis, the investment committee accepts or rejects the proposal. For loans exceeding 300,000 Euro, the approval of ENISA's board is also required. Second, in some cases, the company had not even been created, and the entrepreneurs applying for the PL had not gone further in the process of creating the company, which is required for the PL to be granted. Another reason for the lower acceptance rate is the requirement of a parallel capital increase. Some companies are not able (or willing) to do that. This requirement implies raising equity for a similar amount to that of the loan, which serves as a proof of the applicant's commitment to the business plan.

Since 2005, ENISA has sharply increased the number of PLs granted to entrepreneurial ventures. It granted more than 5000 PLs through the end of 2017. In particular, in our study we focus on companies that received their first loan between 2005 and 2011 from two programs targeted at different entrepreneurial venture categories: high-technology firms (*EBT program*) and high-growth entrepreneurial ventures (*PYME program*).[1] The PLs' maturities range from 4 to 9 years, and their grace periods range from 1 to 7 years.

In the period from 2005 to 2011, 293 firms received PLs that amounted to 99.3 million Euros from the EBT program and 466 firms were granted 175.2 million Euros from the PYME program (Source: ENISA). Under a strict non-disclosure agreement, ENISA provided full information about each loan, including the name of the firm that received the loan, the firm's location and activity sector, the principal of the loan, the date in which the loan was granted, the loan's grace period (if any), the loan's maturity, the loan's status as of December 2017, and the amount reimbursed until that date. We find that the amounts reimbursed to ENISA until that date were 74.8 million Euros (74.97% of the amount committed) for the EBT program and 108.5 million Euros (61.82%) for the PYME program.

We estimate the cost of the program per Euro lent considering two components: credit losses and ENISA personnel costs. This is a conservative estimate, because it does not take into account any interest received by ENISA on the PLs, which can compensate a large fraction of these costs and, indeed, once interest income is considered, ENISA declared positive net profits (Source: ENISA's annual reports) in each year of our observation period except for 2011.[2] Average credit losses on PLs can be estimated by looking at reimbursements for the loans granted in the period 2005–2008, which reached maturity by the end of 2017. The amount reimbursed on these PLs was 75.94% of the 81.9 million Euro granted. This means that a conservative estimate of the taxpayer cost of ENISA PLs is approximately 24 cents per Euro of loan principal (or 66 million Euros for the two programs over the entire period analyzed in this paper). Regarding personnel costs, the average payroll expenses faced by ENISA in the period 2005–2011 was 3.5 cents per Euro of loan principal lent in the same period. A conservative estimate of the total cost of PLs to the taxpayer is 27.5 cents per Euro lent.

3.2. Sample description

We obtained accounting data around the loan event for a sample of 512 beneficiaries, which represent 67.5% of the population of treated companies. Beneficiaries in this sample are representative of the initial population of treated firms, and we cannot reject the null hypothesis that their distribution across industries ($\chi 2(8) = 1.88$) and NUTS2 regions ($\chi 2(16) = 2.31$) is the same as that of the population of treated companies.

To control for the counterfactual, we collect accounting data for a randomly extracted control group of 9,050 non-treated SMEs founded in Spain between 2003 and 2011. The distribution of both treated and control-group companies is reported in Table 1.

The treated companies are most commonly found in the Information and Communication Technology (23.44%), Manufacturing (21.48%) and Other Services (21.48%) industries. These sectors are also the three most important sectors for the control group companies (17.7%, 20.50% and 33.55%, respectively). The least common sector for treated companies in our sample is Primary & Utilities, which represents only 0.78% of the treated companies and 6.19% of the control group companies. Slightly more than half the treated companies in our sample are located in Catalonia (32.23%) or Madrid (25.98%), which also host the most non-treated firms (23.52% and 20.71%, respectively). Finally, we observe that the number of treated companies in our sample grew from 49 that received a loan in 2005–2007 to 316 that received a loan

[1] A third program, JOVENES, was launched in 2010 but is too recent to be included in our analysis.

[2] The fact that ENISA is running at profit suggests private intermediaries, possibly because of capital requirements, are rationing capital markets. We thank an anonymous referee for pointing this out.

Table 1
Distribution of observations by industry, region and year.

	ENISA-backed		Control group	
	No	%	No	%
Industry				
ICT	120	23.44	1602	17.70
Other Services	110	21.48	3036	33.55
Manufacturing	110	21.48	1855	20.50
Pharma and R&D	70	13.67	851	9.40
Commerce	49	9.57	793	8.76
Services	35	6.84	71	0.78
Hotel & Leisure	9	1.76	217	2.40
Transport	5	0.98	65	0.72
Primary & Utilities	4	0.78	560	6.19
Region				
Catalonia	165	32.23	2129	23.52
Community of Madrid	133	25.98	1874	20.71
Andalusia	44	8.59	1746	19.29
Basque Country	36	7.03	683	7.55
Valencian Community	33	6.45	505	5.58
Aragon	19	3.71	351	3.88
Galicia	7	1.37	414	4.57
Rest of Spain	75	14.65	1348	14.89
Loan year				
2005–2007	49	9.57		
2008-2009	147	28.71		
2010-2011	316	61.72		
Total	512	100	9050	100

This table shows the distribution of ENISA-backed and control group companies by industry, region and – for ENISA-backed loans only – loan year.

between 2010 and 2011, reflecting the increasing activity of ENISA during the period.

The descriptive statistics and correlations for the main variables used in our study are reported in Table 2. The companies in our sample have an average of 6.40 employees and sales of 796,300 Euros. Both size variables exhibit substantial variation across the sample, as illustrated by both the standard deviation and the min-max range. The growth in employment and sales are calculated as the year-on-year difference in the logarithm of the relevant variable and are winsorized at the 5% threshold to reduce the impact of outliers. The average growth in employees is 4.78%, and the average growth in sales is 8.73%. On average, the sample companies are 5.0 years of age, with a range of variation between 1 and 19.

ENISA loans correspond to an average principal value of 281,500 Euros.[3] There is a substantial variation in the size of ENISA loans, which range between 27,000 and 1,500,000 Euros. It is interesting to note, in Panel B of Table 2, that *Loan Amount* is positively and significantly correlated with both employees ($\rho = 0.41$, p-value < 1%) and sales ($\rho = 0.34$, p-value < 1%). However, there is no significant correlation between the amount of the loan and the growth rate of companies, which means that larger loans are given to larger companies but not to those companies that are already growing faster than average.

3.3. Methodology

We follow the identification strategy used by Brown and Earle (2017). The empirical model estimates the absolute growth in employment produced by a participative loan. Formally, the model is as follows:

$$\Delta Size_i = \alpha + \beta \bullet Loan\ amount_i + \gamma \bullet Ln(Age_i) + \varphi \bullet Ln(Age_i)^2 + \delta_{reg} + \theta_{ind} + \tau_t + \varepsilon_i \quad (1)$$

where $\Delta Size$ is the difference between the average size (number of employees or sales) in the two years following the loan year and the average size in the two years before loan issuance,[4] *Loan amount* is the principal amount (in million Euro) of the PL, *Age* is the age of the firm in years; and δ_{reg}, θ_{ind}, *and* τ_t are region, industry and year dummies, respectively.

The parameter of interest in Eq. (1) is β, which estimates how the size variable is affected by the size of the loan. When the dependent variable is $\Delta Employees_i$, β indicates how many jobs are created per million Euros granted in the PL. When the dependent variable is $\Delta Sales_i$, β indicates how many millions of Euros of sales are obtained per million Euros granted in the PL. Because the selection process is not random, we must control for observable and non-observable differences between the treated and non-treated companies.

To control for the selection on observables, we resort to propensity-score matching. Each treated company is matched to three control group companies (with replacement) for the year before the PL was obtained. Matching is performed using nearest-neighbor propensity-score matching. Propensity scores are calculated separately for each loan year (2005–2011) using a probit model and including the following characteristics in the previous year: $Ln(Sales)$, $Ln(Employees)$, $Ln(Age)$, and industry and region dummies.

We can evaluate the effectiveness of the propensity-score matching (and have initial evidence about the effect of PL on growth) by looking at the average size of treated and matched companies around the event. In Table 3, we report $Ln(Employees)$ and *Ln(Sales)* of the treated and matched companies at the time of matching (*T*), two years before matching (*T-2)* and 2 years after matching ($T + 2$). At time *T*, the average *Ln(Employees)* is 1.909 for treated companies and 1.912 for matched companies, with a difference (-0.003) that is not statistically different from 0. The average *Ln(Sales)* is 11.573 for treated companies and 11.544 for matched companies, with a difference (0.028) that is not statistically different from 0. This lack of difference is expected after propensity-score matching: treated and matched companies are similar in terms of size at the time of matching.

Two years after the event, the average *Ln(Employees)* and *Ln(Sales)* for treated companies (2.471 and 13.036) are larger than those of matched companies (1.969 and 12.509), with a difference (0.503 and 0.527) that is positive and statistically significant (p-value < 0.1%). These results suggest that treated companies are significantly larger than matched companies 2 years after the event. Combining this with the fact that these companies had similar size at the time of matching, we have some preliminary evidence that treated companies grow faster than matched companies.

It is also interesting to look at what occurs in the two years before the event. In *T-2*, the average *Ln(Employees)* and *Ln(Sales)* for treated companies (1.997 and 12.241) are close to those of for matched companies (1.881 and 12.518), and the difference (0.116 and -0.277) is not statistically significant. In other words, we do not find evidence that treated companies grew more quickly than matched companies in the two years before the loan (in which case they would be significantly smaller than matched companies).

Overall, these results provide evidence that propensity-score matching is effective in identifying matched companies that are similar to the treated companies at the time of matching and provides preliminary evidence that the treated companies grow more quickly than similar non-treated companies after, but not before, the treatment.

The main shortcoming of the propensity-score matching approach is, however, that its validity relies on the strong ignorability assumption, which means that the treated and control group companies should differ only in observable characteristics (i.e., sales, employees, region, industry and age) and that no unobservable characteristics affecting the outcome differ systematically between the two groups. This assumption

[3] When a company receives multiple ENISA loans during the same calendar year, the principal amount is aggregated.

[4] The variable is winsorized at the 5% threshold to reduce the impact of outliers.

Table 2
Descriptive statistics and correlations.

Panel A: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Employees	6.4038	30.584	0	2,5940
Emp. Growth	0.0478	0.3241	−0.6932	0.6931
Sales	0.7963	5.1808	0	434.97
Age	4.9922	2.7189	1	19
Sales growth	0.0873	0.7027	−1.3863	1.7631
ENISA	0.0501	0.2182	0	1
Loan amount	0.2815	0.1867	0.0270	1.5000

Panel B: Correlation matrix

	Employees	Emp. growth	Sales	Sales growth	ENISA	Loan amount
Emp. Growth	0.0650*	1.0000				
Sales	0.5325*	0.0330*	1.0000			
Sales growth	0.0333*	0.4184*	0.0417*	1.0000		
ENISA	0.1145*	0.0407*	0.0883*	0.0528*	1.0000	
Loan amount	0.4099*	−0.0907	0.3441*	−0.0137	0.0005	1.0000
Age	0.0818*	−0.2105*	0.0722*	−0.2466*	0.1955*	0.1757*

Legend: The tables report the descriptive statistics of (Panel A), and correlations between (Panel B), the variables used in this study. *Employees* is the number of a firm's employees. *Sales* is firm's sales in million Euro. *Emp. growth* and *Sales growth* are logarithmic growth from the previous year of employees and sales respectively. *ENISA* is a dummy variable equal to 1 after a firm receives a PL from ENISA. *Loan amount* is the amount (in million Euro) a firm receives from ENISA PLs in a given year (the descriptive statistics for the variable are only reported for beneficiaries, i.e., excluding all firm-year observations in which the variable is, by definition, equal to zero). *Age* is the firm's age (in years). * indicates correlations significant at the 1% level.

Table 3
Ln(Employees) and Ln(Sales) of treated and matched firms before, at, and after matching.

	Employees			Sales		
	(1)	(2)	(3) = (1)-(2)	(4)	(5)	(6) = (4)-(5)
	Treated	Matched	Difference	Treated	Matched	Difference
2 years before matching (T-2)	1.997***	1.881***	0.116	12.241***	12.518***	−0.277
	(0.076)	(0.069)	(0.103)	(0.247)	(0.299)	(0.299)
At matching (T)	1.909***	1.912***	−0.003	11.573***	11.544***	0.028
	(0.056)	(0.052)	(0.076)	(0.184)	(0.174)	(0.254)
2 years after matching (T + 2)	2.471***	1.969***	0.503***	13.036***	12.509***	0.527***
	(0.047)	(0.052)	(0.070)	(0.107)	(0.106)	(0.151)

Legend: The table reports the average *Ln(Employees)* and *Ln(Sales)* of treated firms and firms matched using a propensity score 2 years before matching (T-2), at the time of matching (*T*), and 2 years after matching (*T + 2*). The outcome variables are *Ln(Employees)*, the natural logarithm of the number of a firm's employees and *Ln (Sales)*, the natural logarithm of the firm's sales (in Euro). *Difference* is the difference in *Ln(Employees)* – column 3 – and *Ln(sales)* – column 6 – between treated and matched firms. Standard errors are in round brackets. ***: p-value < 0.1%.

is generally violated when selection is based on non-observable information (e.g., firms that have better expectations about future growth may be more prone to look for and obtain PLs). Violation of the strong ignorability assumption may bias the estimation of Eq. (1) in a way that is equivalent to the omission of a variable in an OLS estimation (Li and Prabhala, 2007). To overcome this potential bias, we estimate Eq. (1) using a two-step IV model. In the first step, we adopt two instruments that measure the relative frequency of the ENISA loans in the province (NUTS3) and industry (2-digit NACE code) in the previous year. These instruments are theoretically valid because there is no reason to believe that unobserved information about a given company depends on the frequency of ENISA loans given to firms in the same province or in the same industry in the previous year. The instruments are also empirically strong because in the first-step estimations, their parameters have the expected sign (positive), and we can reject the null hypotheses that these parameters are jointly equal to 0 with a p-value < 1%.[5]

[5] See Section 5.4 for further discussion about instrument validity and strength.

To test the effectiveness of PLs on different groups of companies (i.e., small, young and high-tech firms) or time period (the GFC) the *Loan Amount* in Eq. (1) interacts with several dummies that identify beneficiaries that: are below the median age or size, operate in an industry that is classified by Eurostat as a high-tech manufacturing sector or a knowledge-intensive services sector (Eurostat, 2015), and received the PL during the GFC.

4. Results

4.1. Effect of participative loans

We report in Table 4 the results of the analysis on a firm's growth in employment (Panel A) and sales (Panel B) after the receipt of a PL. The results clearly indicate that the estimated coefficient of the *Loan amount* is positive and statistically significant (p-value < 1% or better) regardless of the estimation method (propensity-score matching or 2-stage least squares), the set of covariates, and the dependent variable (employees or sales). These results lend evidence to our expectation that PLs boost employment and sales growth in the treated companies.

Table 4
Loan amount and growth in employment and sales.

Panel A: employment growth

	Propensity-score matching			2-stage least squares		
	(1)	(2)	(3)	(4)	(5)	(6)
Loan amount	12.674***	12.6465***	12.1481***	20.4725***	16.4008***	14.7352***
	(3.110)	(3.0046)	(3.1109)	(2.5380)	(2.2611)	(3.9424)
Ln(Age)		−1.5219**	−1.8657*		−1.7808***	−1.5490***
		(0.5001)	(0.9066)		(0.1766)	(0.1783)
$Ln(Age)^2$		0.8229	0.7305		0.5507	0.1374
		(0.9529)	(0.9800)		(0.4026)	(0.4913)
Fixed effects						
Industry	No	No	Yes	No	No	Yes
Region	No	No	Yes	No	No	Yes
Year	No	No	Yes	No	No	Yes
Observations	933	933	933	13014	13014	13014

Panel B: sales growth

	Propensity-score matching			2-stage least squares		
	(1)	(2)	(3)	(4)	(5)	(6)
Loan amount	1.1422**	1.1065**	1.0867**	1.7665***	1.2836***	1.9688***
	(0.3871)	(0.3848)	(0.4025)	(0.2679)	(0.2470)	(0.4636)
Ln(Age)		−0.3331***	−0.3614**		−0.2367***	−0.2053***
		(0.1002)	(0.1100)		(0.0212)	(0.0226)
$Ln(Age)^2$		0.2907*	0.3108*		0.1968***	0.0443
		(0.1231)	(0.1281)		(0.0478)	(0.0641)
Fixed effects						
Industry	No	No	Yes	No	No	Yes
Region	No	No	Yes	No	No	Yes
Year	No	No	Yes	No	No	Yes
Observations	962	962	962	13014	13014	13014

Legend: The table reports the effect of loans on employment growth (Panel A) and sales growth (Panel B), calculated with propensity-score matching (columns 1–3) and 2-stage least squares (columns 4–6). Employment growth is calculated as the difference between the average number of employees in the two years after the event (*T + 1* and *T + 2*) and the average number of employees in the two years before the event (*T-1* and *T-2*). Sales growth is calculated as the difference between the average sales (in million Euro) in the two years after the event (*T + 1* and *T + 2*) and the average sales (in million Euro) in the two years before the event (*T-1* and *T-2*). *Loan amount* is the amount (in million Euro) a firm receives from ENISA PLs in a given year. *Ln(Age)* is the natural logarithm of the firm's age (in years). Robust standard errors are in round brackets. The instrumental variables for the 2-stage least squares method are the lagged frequencies of ENISA loans in the province and industry of the focal firm.

* p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

The magnitude of the effect is economically significant. If we take the models with the most complete set of covariates (columns 3 and 6), the estimated coefficient of the *Loan amount* is between 12.1 (propensity-score matching) and 14.7 (2-stage least squares) in Panel A and between 1.09 and 1.97 in Panel B. Therefore, this means that other things being equal and controlling for observable and unobservable heterogeneity, 1 million Euros in ENISA loans generated between 12.1 and 14.7 jobs and between 1.09 and 1.97 million Euros in sales in the two years following loan issuance (compared to average employment and sales in the two years before loan issuance). This effect is substantially larger than that found by Brown and Earle (2017) for guaranteed loans in the US, which create between 3 and 3.5 jobs in the three-year period following the loan. This is consistent with the fact that ENISA loans are granted to firms that are younger and smaller and for which in principle, the effect of PLs should be larger (as discussed in the next section) and the loans riskier.

4.2. Moderating effects of age, size, sector and crisis

In this section, we test the extent to which PLs are more effective for subsamples of companies for which financial constraints are more pronounced on average either because of information asymmetries (young companies, small companies, and companies operating in high-tech sectors) or because of the time period (during the global financial crisis). The results of the analyses are reported in Table 5.

The results show that PLs are more effective when they are addressed to companies that are more exposed to financial constraints. For an equal amount, PLs create substantially more jobs in young (49.7, p-value < 5%) and small (45.1, p-value < 5%) companies, in companies that operate in high-tech sectors (19.2, p-value < 5%), and in companies that obtained a PL during the financial crisis (32.5, p-value < 1%). For an equal amount, PLs also generate a substantially larger increase in sales in young (5.64, p-value < 5%) and small (7.73, p-value < 1%) companies and in companies that obtained a PL during the financial crisis (3.59, p-value < 5%).[6] The results are both large in magnitude and statistically significant at customary confidence levels.

[6] The increase in sales is positive but only close to significance in high-tech vs. other sectors, possibly because sales growth takes a longer time to materialize in high-tech sectors.

Table 5
Effect of ENISA loans on young, small and high-tech firms and during the financial crisis.

Panel A: employment growth

	(1) Age	(2) Size	(3) Industry	(4) Crisis
(Loan amount) · (Young)	49.6784*			
	(19.2996)			
Young	0.1958			
	(0.1445)			
(Loan amount) · (Small)		45.1041*		
		(18.7184)		
Small		−3.4787***		
		(0.4128)		
(Loan amount) · (High-tech)			19.2405*	
			(8.0484)	
High-tech			0.2060	
			(0.1405)	
(Loan amount) · (Crisis)				32.4988**
				(12.3052)
Crisis				−0.5369**
				(0.1709)
Loan amount	8.9128†	−7.5942	1.8287	−5.2392
	(4.6918)	(9.8245)	(7.0647)	(10.8652)
Ln(Age)	−0.8291*	−1.7912***	−1.5394***	−1.5594***
	(0.3622)	(0.1787)	(0.1837)	(0.1830)
$Ln(Age)^2$	−0.0189	1.0041	0.1391	0.3417
	(0.4915)	(0.6816)	(0.4844)	(0.6013)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	No	Yes
Year	Yes	Yes	Yes	Yes
Observations	13014	13014	13014	13014

Panel B: Sales growth

	(1) Age	(2) Size	(3) Industry	(4) Crisis
(Loan amount) · (Young)	5.6371*			
	(2.4817)			
Young	0.0322†			
	(0.0175)			
(Loan amount) · (Small)		7.7304**		
		(2.6346)		
Small		−0.4570***		
		(0.0578)		
(Loan amount) · (High-tech)			1.5061	
			(1.0053)	
High-tech			0.0831***	
			(0.0199)	
(Loan amount) · (Crisis)				3.5900*
				(1.5220)
Crisis				−0.1214***
				(0.0221)
Loan amount	1.3022*	−1.8477	0.8687	−0.2254
	(0.5488)	(1.4181)	(0.8524)	(1.3168)
Ln(Age)	−0.1070*	−0.2381***	−0.2046***	−0.2064***
	(0.0449)	(0.0241)	(0.0226)	(0.0235)
$Ln(Age)^2$	0.0169	0.2144*	0.0509	0.0659
	(0.0630)	(0.0997)	(0.0618)	(0.0784)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	No	Yes
Year	Yes	Yes	Yes	Yes

(*continued on next page*)

Table 5 (*continued*)

Panel B: Sales growth	(1) Age	(2) Size	(3) Industry	(4) Crisis
Observations	13014	13014	13014	13014

Legend: The table reports the effect of loans on employment growth (Panel A) and sales growth (Panel B), calculated using 2-stage least squares. Growth in employment is calculated as the difference between the average number of employees in the two years after the event (*T + 1* and *T + 2*) and the average number of employees in the two years before the event (*T-1* and *T-2*). Sales growth is calculated as the difference between the average sales (in million Euro) in the two years after the event (*T + 1* and *T + 2*) and the average sales (in million Euro) in the two years before the event (*T-1* and *T-2*). *Loan amount* is the amount (in million Euro) a firm receives from ENISA PLs in a given year. *Ln(Age)* is the natural logarithm of the firm's age (in years). *Young* is a dummy variable equal to one for firms that are younger than the median age of treated companies at the time of treatment. *Small* is a dummy variable equal to one for firms whose total assets are smaller than the median industry-adjusted total assets of treated companies at time of treatment. *High-tech* is a dummy variable equal to one for firms that operate in an industry that is classified in the high-tech manufacturing or knowledge-intensive services sectors by Eurostat (Eurostat, 2015). *Crisis* is a dummy variable equal to one for firms that received treatment during the GFC. Robust standard errors are in round brackets. The instrumental variables for the 2-stage least squares method are the lagged frequencies of ENISA loans in the province and industry of the focal firm. †: p-value < 10%, *: p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

Table 6
Loan amount and growth: different time intervals and matching model.

	Employees			Sales		
	(1) IV on (T + 1)-(T-1)	(2) IV on (T + 3)-(T-3)	(3) Matching past growth	(4) IV on (T + 1)-(T-1)	(5) IV on (T + 3)-(T-3)	(6) Matching past growth
Loan amount	8.5575***	25.2872***	12.6871***	0.6981***	3.6678***	1.3978***
	(1.9499)	(7.6646)	(2.8288)	(0.2061)	(1.0641)	(0.3638)
Ln(Age)	−1.0930***	1.2304	−3.0104***	−0.1286***	0.2002	−0.2261*
	(0.0564)	(1.3604)	(0.8091)	(0.0065)	(0.2007)	(0.0881)
$Ln(Age)^2$	0.6910***	−5.4624†	1.3066†	0.1155***	−0.8557*	0.1553
	(0.1048)	(2.7891)	(0.7909)	(0.0124)	(0.4143)	(0.1009)
Fixed effects						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25249	5477	932	25249	5477	943

Legend: The table reports the effect of loans on growth in employees (columns 1–3) and in sales (columns 4–6) using 2-stage least squares (columns 1, 2, 4 and 5) and propensity-score matching (columns 3 and 6). Growth is calculated as the difference between the average number of employees (columns 1–3) and average sales in Euro million (columns 4–6) in a time interval after and before the event. The time interval is three years in columns 2 and 4 and one year in the other columns. *Loan amount* is the amount (in million Euro) a firm receives from ENISA PLs in a given year. *Ln(Age)* is the natural logarithm of the age (in years) of a firm. Robust standard errors are in round brackets. The instrumental variables for the 2-stage least squares method are the lagged frequencies of ENISA loans in the province and industry of the focal firm. The propensity-score matching method used in columns 3 and 6 includes lagged growth of the focal company. †: p-value < 10%, *: p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

5. Robustness checks and additional evidence

5.1. Robustness

We perform numerous robustness analyses to confirm the reliability of our results and report them in Table 6. First, we estimate the effect of PLs using different time windows around the event. The choice of the time window is determined by a tradeoff between having an observation period that is long enough to capture the effect of PLs and preserving enough observations for the estimates. In columns 1 and 4 of Table 6, we report the estimates based on the difference between employees (column 1) and sales (column 4) one year after loan issuance (*T + 1*) and one year before loan issuance (*T-1*). Shortening the time period around the loan allows us to base our estimates on nearly twice as many observations (25,249 observations) than when using averages for the two years after and before loan issuance (13,014 observations, as reported in Table 4). However, a shorter time window could lead to a downward estimate of the full effect of PLs because the effect takes longer to fully materialize. Our estimates indicate that for each million Euros granted in a PL, companies have an additional 8.6 (p-value < 0.1%) jobs and 698,100 Euros (p-value < 0.1%) in sales in T + 1 than in T-1.

In columns 2 and 5, we illustrate the results in which the dependent variable is the firm's average number of employees (column 2) and sales (column 5) in the three years after loan issuance (*T + 1* to *T + 3*) compared to the number of employees in the three years before loan issuance (*T-3* to *T-1*). While a longer time window allows us to better assess the effect of PLs, the number of usable observations in this window drops to 5,477 because we can now include in our sample only companies with 7 years of consecutive observations, and our sample is mostly composed of young SMEs, which may not meet these requirements. Our estimates indicate that in the three years after PL issuance, for each million Euros of loan beneficiaries create an average of 25.3 (p-value < 0.1%) jobs and have 3,667,800 Euros (p-value < 0.1%) of additional sales.

Finally, we do not find evidence of a correlation between past growth and loan amount (Table 2 panel B) or of any pre-treatment abnormal growth of treated companies (Table 3). However, for the sake of completeness, in columns 3 and 6 we extend the propensity-score matching method to include the growth in employment and sales before the event (i.e., between T-2 and T-1) as an additional matching variable. Our results hold virtually unchanged: this augmented propensity-

Table 7
ENISA loans and growth in employment and sales: Dynamic panel data models.

	Employment growth			Sales growth		
	(1) OLS	(2) Fixed effects	(3) GMM	(4) OLS	(5) Fixed effects	(6) GMM
$Ln(Size_{-1})$	−0.0466***	−0.2549***	−0.0890**	−0.0723***	−0.1421***	−0.1674***
	(0.0041)	(0.0087)	(0.0284)	(0.0036)	(0.0071)	(0.0295)
$ENISA_{t-1}$	0.0798***	0.0528***	0.1058***	0.2191***	0.1191***	0.1796***
	(0.0123)	(0.0153)	(0.0315)	(0.0247)	(0.0358)	(0.0460)
Ln(Age)	−0.1466***	−0.1722***	−0.1194*	−0.3358***	−0.7004***	−0.2701**
	(0.0107)	(0.0304)	(0.0480)	(0.0214)	(0.0616)	(0.0881)
Fixed effects						
Industry	Yes	No	Yes	Yes	No	Yes
Region	Yes	No	Yes	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8850	8850	8850	8943	8943	8943
AR(1)			−14.1296***			−1.2143
AR(2)			−1.6197			0.8627
Hansen			160.2 [150]			140.5 [165]

Legend: The table reports the estimates of dynamic panel-data models using OLS (columns 1 and 4), fixed effects (columns 2 and 5) and two-step system GMM with finite sample correction (columns 3 and 6). The dependent variable for columns 1–3 is the increase in *Ln(Employees)* – the natural logarithm of the number of a firm's employees – relative to the previous year. The dependent variable for columns 4–6 is the increase in *Ln(Sales)* – the natural logarithm of firm's sales (in Euro) – relative to the previous year. *ENISA* is a dummy variable equal to 1 after a firm receives a PL from ENISA. *Ln(Age)* is the natural logarithm of the firm's age (in years). Robust standard errors are in round brackets. Degrees of freedom are in squared brackets. *: p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

score matching method predicts that 1 million Euros of PL will result in an additional 12.69 (vs. 12.15 in Column 3 in Panel A of Table 4) jobs and 1.40 (vs. 1.09 in Column 3 in Panel B of Table 4) million Euros in sales.

5.2. Dynamic panel data models

To provide additional evidence, we adopt a different econometric strategy to estimate the effect of PLs on employment and sales growth. We estimate a series of augmented Gibrat-law panel-data models (Evans, 1987) derived from the model specification used by Grilli and Murtinu (2014). This model is standard in the industrial organization literature on firm growth (e.g., Sutton, 1997) and allows us to test whether the growth rates of ENISA-backed firms persistently increase after a PL is issued relative to non-ENISA-backed firms. The dependent variable is the logarithmic growth in the number of employees and sales,[7] and our control variables include the logarithm of size (employees or sales) in the previous year, *Ln(Age)*, and regional, industry and year fixed effects. The variable of interest is a dummy variable ($Enisa_{t-1}$) that switches from 0 to 1 the year after a company receives a PL from ENISA. Using OLS and fixed effects to estimate Gibrat-law models may result in biased estimates of the parameters (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Moreover, these methods either do not (OLS) or only partially (fixed-effects) control for unobserved heterogeneity. We address these problems by using the system generalized method of moments (GMM-SYS) approach (Blundell and Bond, 1998). Specifically, we implement the GMM-SYS estimation procedure with moment conditions for endogenous variables (i.e., lagged size and ENISA) starting from t-2 for first-differenced instruments in level equations and t-3 for level instruments in first-differenced equations. We also include the finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005). The results of these models are reported in Table 7.

The ENISA coefficient is significant at the 0.1% confidence level for both employment and sales in each of the three specifications. Based on the GMM estimates, the additional annual growth of ENISA-backed companies is 10.6% for employment and 18.0% for sales. Regarding the control variables, growth tends to be faster for smaller companies and slows (at a declining rate) as the company matures.

5.3. Survival

In this section, we explore the extent to which PLs affect the survival of treated companies. A full-fledged analysis of this aspect is beyond the scope of this paper, mostly because of the difficulty in obtaining unbiased data about failed companies from Orbis. We were able to retrieve historical data on all companies existing in 2010, which includes all companies that failed in later years. We drop from the sample all beneficiaries that received PLs before 2010 and look at the probability that the remaining beneficiaries failed in later years compared to other SMEs and with matched companies.

We estimate a probit model on the probability of bankruptcy and control for numerous firm characteristics that are typically (Altman, 1968; Altman and Sabato, 2007) associated with survival: liquidity (working capital/total assets), productivity (EBIT/Total assets), leverage (debt/total assets), capital-turnover ratio (sales/total assets), asset tangibility (intangible assets/total assets), age, and size. We also include in the estimates a full set of industry and region fixed-effects. We add to this specification a dummy variable (ENISA) that is equal to 1 for ENISA-backed companies, and – in a further specification – the size of the PL scaled by the total assets (Loan amount/Total assets). Results are reported in Table 8 for the whole sample (columns 1 and 3) and for the subset of propensity-score matched firms (columns 2 and 4).

Overall, the models estimated in Table 8 are in line with expectations. The probability of bankruptcy declines (p-value < 5% or better) with productivity (EBIT/Total assets), increases with leverage (p-value < 5% or better), and decreases with firm size (p-value < 5% or better). We also find weak evidence that bankruptcy increases with intangibility and asset turnover (p-value below threshold only in some specifications). More importantly, we cannot reject the null hypothesis that once we control for these characteristics, PL beneficiaries have the same probability of going bankrupt as other SMEs and matched companies.

We reiterate that these results are only based on a subsample of companies and that a more comprehensive and robust analysis would be necessary to shed light on this issue. However, at this stage we can

[7] The variable is winsorized at the 5% threshold to reduce the impact of outliers.

Table 8
Survival analysis after the receipt of an ENISA loan.

	(1) All sample	(2) ENISA and matched companies	(3) All sample	(4) ENISA and matched companies
Working capital/ Total assets	0.0373	−0.3170	0.0373	−0.3364
	(0.0692)	(0.2772)	(0.0692)	(0.2784)
EBIT/Total assets	−0.2062***	−0.5452**	−0.2033***	−0.4996*
	(0.0545)	(0.2026)	(0.0546)	(0.2108)
Leverage	0.4182*	1.8397**	0.4141*	1.8403**
	(0.1634)	(0.5924)	(0.1634)	(0.5959)
Sales/Total assets	0.0313*	0.0005	0.0314*	−0.0013
	(0.0122)	(0.0534)	(0.0122)	(0.0533)
Intangible assets/Total assets	0.2952†	0.3180	0.2917	0.3063
	(0.1772)	(0.4000)	(0.1775)	(0.3990)
Ln(Age)	−0.0630	0.1608	−0.0595	0.1877
	(0.0406)	(0.1643)	(0.0408)	(0.1768)
Ln(Sales)	−0.0981***	−0.0825*	−0.0976***	−0.0808*
	(0.0135)	(0.0381)	(0.0135)	(0.0378)
ENISA	0.1891	0.1584	0.0703	0.0748
	(0.1208)	(0.1695)	(0.1979)	(0.2464)
Loan amount/ Total assets			0.6366	0.4805
			(0.8044)	(1.0251)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Observations	5390	512	5390	512

Legend: The table reports the estimates of a probit model in which the dependent variable is a dummy equal to one for sample companies that failed. The sample includes all companies existing in 2010 (columns 1 and 3) and all ENISA companies existing in 2010 and their matched companies (columns 2 and 4). *Working capital/Total assets* is the ratio between the firm's working capital and total assets. *EBIT/Total assets* is the ratio between the firm's EBIT (earnings before interest and taxes) and total assets. *Leverage* is the ratio between the firm's financial liabilities and total assets. *Sales/Total assets* is the ratio between the firm's sales and total assets. *Intangible assets/Total assets* is the ratio between the firm's intangible assets and total assets. *Ln(Age)* is the natural logarithm of firm's age (in years). *Ln(Sales)* is the natural logarithm of firm's sales (in Euro). *ENISA* is a dummy variable equal to 1 after a firm receives a PL from ENISA. *Loan amount/Total assets* is the ratio between the size of the ENISA PL and firm's total assets. Robust standard errors are in round brackets. *: p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

say that there is no compelling evidence that PLs increase the likelihood of bankruptcy for beneficiaries. This is possibly the result of the positive correlation between interest payments and profits, which means that the financial burden of PLs will be reduced when a firm faces a decline in profits.

5.4. Spillover effect

Our analysis does not aim to provide a comprehensive measure of the welfare effect of PLs, but it is still interesting to look at the presence of spillovers. In particular, it is important to understand whether PL beneficiaries grow at the expense of other companies, in which case we would observe a negative spillover effect. To verify the existence of negative spillovers, we perform an analysis of firm growth as a function of the intensity of ENISA loans. We estimate a growth model along the lines of the analysis reported in Section 4.1. Results are reported in Table 9. The dependent variable of the regression is employment (columns 1 and 2) and sales (columns 3 and 4) growth. We control for age and include time fixed effects. The main difference from the analysis in Section 4.1 is that instead of including the ENISA dummy, we include two measures of ENISA loan intensity at the local level (annual number of ENISA loans in the NUT3-level province), and industry (annual number of ENISA loans in the NACE 2-digit-level industry).[8] We then estimate each growth model both on the sample of treated and matched companies and on a sample that only includes the matched companies. This latter regression should give us an indication of the extent to which the growth of non-beneficiaries is affected by ENISA loan intensity.

Table 9
Spillover of ENISA loans on employment and sales growth.

	Employment growth		Sales growth	
	(1) Treated and matched	(2) Matched only	(3) Treated and matched	(4) Matched only
ENISA loans in province	68.1067*	27.8975	5.3632*	1.6146
	(26.5472)	(23.7594)	(2.6062)	(2.6960)
ENISA loans in industry	17.6209***	−2.1217	1.8510***	0.0337
	(4.5430)	(5.1612)	(0.5120)	(0.6045)
Ln(Age)	−1.5594†	−1.2543	−0.3193**	−0.1348
	(0.8776)	(1.1122)	(0.1074)	(0.1232)
$Ln(Age)^2$	0.2087	−0.5792	0.2355†	−0.0477
	(0.9610)	(2.3371)	(0.1264)	(0.2635)
Fixed effects				
Year	Yes	Yes	Yes	Yes
Observations	933	692	962	692

Legend: The table studies the spillover effect of ENISA loans on employment growth (columns 1–2) and sales growth (columns 3–4). Columns 1 and 3 include both treated companies (i.e., beneficiaries of ENISA loans) and matched companies. Columns 2 and 4 only include matched companies. Employment growth is calculated as the difference between the average number of employees in the two years after the event (*T + 1* and *T + 2*) and the average number of employees in the two years before the event (*T-1* and *T-2*). Sales growth is calculated as the difference between the average sales (in million Euro) in the two years after the event (*T + 1* and *T + 2*) and the average sales (in million Euro) in the two years before the event (*T-1* and *T-2*). *Enisa loans in province* is the number of ENISA loans in the same province (NUTS3 level) as the focal company. *Enisa loans in industry* is the number of ENISA loans in the same industry (NACE 2-digit level) as the focal company. *Ln(Age)* is the natural logarithm of the firm's age (in years). Robust standard errors are in round brackets. †: p-value < 10%, *: p-value < 5%, **: p-value < 1%, ***: p-value < 0.1%.

As expected, in columns 1 and 3, in which we estimate the model on the whole sample, we find that firms in provinces and industries in which ENISA loans are greater grow faster (p-value < 5% for *ENISA loans in province* and p-value < 0.1% for *ENISA loans in industry*). Once we remove from the sample the treated companies (columns 2 and 4), the intensity of ENISA loans ceases to be significant. This result means that ENISA intensity drives firm growth through treated companies but does not affect the growth of non-beneficiaries. In summary, we do not find evidence of negative spillovers for firms in the same province and industry as PL beneficiaries.

It is interesting to observe that results in Table 9 support the appropriateness of the instruments we use in our 2SLS (Table 4) and GMM (Table 7) analysis: ENISA loan intensity affects growth through treated companies (for which the ENISA dummy is 1) but not through non-

[8] We replicate this analysis using the ENISA loan amounts instead of loan count. Results, which are not shown for the sake of brevity but are available from authors upon request, are fully consistent with those reported in Table 9.

Table 10
Summary of the main results of the paper.

	Employees	Sales
Growth per million Euro of principal [a]	12.1–14.7 jobs	1.09 - 1.97 million Euro
Cost of growth for the taxpayer [b]	19,000–23,000 Euro per job	140,000–275,000 Euro per million Euro in sales
Increase in annual growth for beneficiaries [c]	10.6%	18.0%
Growth larger for younger beneficiaries [d]	Yes	Yes
Growth larger for smaller beneficiaries [d]	Yes	Yes
Growth larger for high-tech beneficiaries [d]	Yes	No evidence
Growth larger for crisis beneficiaries [d]	Yes	Yes
Spillover effect at local or industry level [e]	No evidence	No evidence
Difference in survival rate for beneficiaries [f]	No evidence	

Legend: *a*: average in the two years after vs. before the loan, based on Table 4.
b: average in the two years after vs. before the loan, conservative estimate based on Table 4 and aggregate statistics about ENISA loan reimbursement.
c: average effect after the loan based on columns 3 and 6 in Table 7.
d: based on Table 5.
e: based on Table 9.
f: based on Table 8.

treated companies. At the same time, results in Table 9 can also shed some light on another issue that might affect our analysis: the relocation of SMEs. One could argue that SMEs with promising investment ideas could relocate to provinces in which PLs are more easily available. In this case, our instruments would not be valid, because the geographical distribution of companies would not be exogenously determined. Because companies with more promising growth opportunities would relocate to regions with high intensity of ENISA loans, we should observe faster growth in provinces with high ENISA intensity, which is not consistent with the results in Table 9.

6. Discussion and conclusions

There is a general consensus among governments that a gap persists in the availability of long-term financing to entrepreneurial ventures that justifies the existence of special policy measures aimed at addressing this issue. The usual approaches followed include R&D/investment subsidies, subsidized loans, loan guarantees, and direct equity investments (i.e., governmental VC). There is mostly positive evidence on the effect of subsidized loans and loan guarantees, albeit at a high cost, and a negative assessment of governmental VC. In this work, we analyze the effect of a hybrid policy instrument, PLs, on employment and sales growth among entrepreneurial ventures, which exhibits some differences from that of ordinary loans or of equity financing.

To perform matching in our models, we focus on a sample of 512 firms that received a PL from ENISA – a government agency of the Spanish Ministry of Economy, Industry, and Competitiveness – between 2005 and 2011 and a control group of 9, Zúñiga 050 firms. We summarize our main findings in Table 10. Firms receiving PLs from ENISA experience significantly higher growth in employment and sales than do their matched firms. Specifically, after controlling for observable and unobservable heterogeneity, every 1 million Euros granted in an ENISA PL generated between 12.1 and 14.7 jobs and had between 1.09 and 1.97 million Euros in additional sales in the two years following loan issuance (compared to average employment and sales in the two years before loan issuance). The magnitude of the effect is substantially larger than that found by Brown and Earle (2017) for guaranteed loans in the US, which create between 3 and 3.5 jobs in the three-year period after loan issuance. The required principal amount of PLs per job created is then between 68,027 and 82,645 Euro. Because, as illustrated in Section 3.1, a conservative estimate of the taxpayer cost of the program is 27.5 cents per Euro of PL, the taxpayer cost per job can be estimated between 19,000 and 23,000 Euro, not considering income received in the form of fixed and profit-related interest payments. This estimate is similar to the cost per job found by Brown and Earle (2017) for guaranteed loans in the US (between 21,000 and 25,000 USD), with the important difference that loan guarantee programs do not entail any interest income for the guarantor.

Our paper also provides evidence that PLs are more effective for subsamples of companies for which asymmetries in information are more pronounced on average, such as young companies, small companies, companies operating in high-tech sectors and beneficiaries that received a PL during the global financial crisis.

We also perform numerous robustness analyses to confirm the reliability of our results. We document the effect of PLs using different time windows around the event and show that the estimated effect is positive also if we look at 1 and 3 years after the event. One relevant issue for the correct specification of propensity-score matching and IV models is reverse causality. To this extent, we do not find any evidence that larger loans are given to companies that are growing faster, that treated companies grow faster than matched companies before receiving the PL, or that the growth of non-treated companies is affected by the intensity of ENISA loans in the province and industry. Moreover, adding past growth among the matching variables leaves the results qualitatively identical. To this extent, our results suggest that PLs may indeed be beneficial to the economy by changing the growth trajectory of beneficiaries, at least to the extent to which this change is not due to displacement of competitors and is persistent. Our tests on spillovers suggests that such displacements occur, and that growth is genuine.

To test whether the growth rates of PL-awarded firms persistently increase after a PL, we estimate a series of augmented Gibrat-law panel-data models (Grilli and Murtinu, 2014). Our dynamic panel-data analysis confirms that PLs boost annual employment growth by 10.6% and sales by 18.0%. This evidence can be compared to the results obtained by Grilli and Murtinu (2014) on governmental VC. Contrary to our results for PLs, Grilli and Murtinu (2014) do not find evidence of an additional effect of governmental VC on employment growth. Finally, we explore the impact of ENISA loans on survival and find no evidence that once we control for the standard firm characteristics that affect the likelihood of bankruptcy (liquidity, productivity, asset-turnover ratio, asset tangibility, age and size), PL beneficiaries have a different probability of going bankrupt than other SMEs and of matched companies.

Our analysis shows that PLs: have been extremely effective in boosting growth; have a substantial and persistent effect on beneficiaries; are not associated with negative spillovers; are most effective for the firms for which information asymmetries are larger. Overall this suggests that, rather than competing with private sector intermediaries, ENISA is filling an unmet demand for capital from good quality firms.

The main contribution of this work to the entrepreneurial finance literature is the evidence of the positive impact of hybrid instruments on entrepreneurial ventures' growth, which complements the existing evidence on the impact of other policy instruments, such as R&D subsidies, subsidized loans, loan guarantee schemes and governmental VC (Hyytinen and Toivanen, 2005).

This work also has interesting policy implications. Policy makers are increasingly directing their attention to hybrid instruments (OECD, 2015) to design appropriate schemes to support entrepreneurial ventures (Colombo et al., 2016). As a policy instrument, PLs are superior to governmental VC, which does not appear to be an effective tool for creating jobs. PLs are also a cost-effective alternative to subsidized loans and loan guarantee schemes, once we consider that additional income from beneficiary firms' profits was not accounted for in the conservative estimate illustrated in Table 10.

This work has several limitations that can be addressed in future studies. Future research should provide empirical evidence on whether PLs outperform or complement other forms of government intervention and other instruments specifically focused on startups, such as accelerators, business angels and incubators. Future contributions should also test the impact of PLs on other performance measures such as total factor productivity, which is commonly used as a proxy for a firm's innovative activity and reflects how effectively firms use production inputs to produce output relative to other firms that operate in the same industry.

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