EIF Impact Assessment

Working Paper 2025/103

Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania

Fabio Bertoni, Massimo G. Colombo, Anita Quas

Fabio Bertoni

Professor of Finance at SKEMA Business School.

Massimo G. Colombo

Professor of Entrepreneurship, Entrepreneurial Finance and Innovation Economics and Associate Dean for Research and Rankings at Politecnico di Milano, School of Management.

Anita Quas

Associate Professor of Corporate Finance at University of Milan.

Editor:
Helmut Kraemer-Eis
Head of Impact Assessment
Chief Economist

Contact:
European Investment Fund
37B, avenue J.F. Kennedy, L-2968 Luxembourg

Tel.: +352 248581 596
Our markets and impact (eif.org)
Luxembourg, April 2025

Scan above to obtain a PDF version of this working paper

Preface

Small and Medium-sized Enterprises (SMEs) are the backbone of the EU economy. Yet, they often face greater challenges than larger firms, particularly in securing access to finance. These challenges can be ascribed to various issues in credit financing markets (Esho and Verhoef, 2018).

To address these market failures, national and supranational governments and organizations within the EU have introduced financial measures to support SME financing, notably through Public Credit Guarantee Schemes (CGSs). Public CGSs reduce lenders' risk and improve their lending capacity, which in turn enhances the debt financing options available to SMEs (Kraemer-Eis et al., 2018).

EU SME guarantees, funded by the EU and managed by the EIF, play a key role in this area. This policy tool has evolved over the past decades, in line with the European Commission's programming periods.[1] Currently, the EIF manages the deployment of EUR 10bn of EU SME guarantees via the ongoing "InvestEU" programme (2021–2027).

For the EIF, it is not solely about volumes. The focus is on making a tangible impact in the market, especially for SMEs. Thus, assessing the impact of EIF's activities is crucial. Additionally, with the widespread use of guarantee schemes across Europe, there is a growing demand to measure their economic outcomes and impacts.

Ex-post impact assessments, which typically rely on large-scale micro-data, are essential for analysing the medium- to long-term outcomes and impacts of CGSs. However, these assessments present several theoretical and technical challenges, particularly the issue of causal inference.

In recent years, the EIF has earned a strong reputation for conducting impact assessments of policies in support of SME financing, including guarantees and equity schemes. These studies, published in the EIF Working Paper series, employ advanced econometric techniques and benefit from collaboration with recognised academics, adding layers of validation and independence.

This latest analysis focuses on the COSME Loan Guarantee Facility and builds upon previous impact assessments of its predecessor programs (MAP/CIP). Looking ahead, the EIF is committed to further enhancing its approach to impact assessment, also continuously striving to identify innovative solutions to improve its methodological toolbox.

Helmut Kraemer-Eis
Head of Impact Assessment,
Chief Economist, EIF

Simone Signore
Head of Impact Strategy, EIF

[1] EU SME CGSs originated with "SMEG 1998" (under the Growth and Employment Initiative, 1998–2000), followed by "SMEG 2001" (under the 2001–2006 Multi-Annual Programme for Enterprises and Entrepreneurship for SMEs, MAP), the "CIP SMEG" facility (under the Competitiveness and Innovation Framework Programme, 2007–2013), and the "COSME Loan Guarantee Facility" (under the EU Programme for the Competitiveness of Enterprises and Small and Medium-sized Enterprises, 2014–2020).

Executive Summary

In this report, we present the results of the analysis of the treatment effect of the COSME loan guarantee facility (LGF) in four European countries (Greece, Poland, Romania, and Spain) during 2015-2023.

We estimate the treatment effect of guaranteed loans on growth in assets, sales, intangible fixed assets, tangible fixed assets, and labour productivity using both difference-in-difference (diff-in-diff) with Propensity Score Matching in a cross-sectional setting (with a baseline of 3 years after the beginning of the signature year), and fixed-effect panel data models. We also resort to probit and Cox proportional-hazard models to estimate the treatment effect on the survival of guaranteed-loan beneficiaries.

Our key findings show that beneficiaries outgrow their matched counterparts three years after the signature year. The additional logarithmic growth is 13.3 percentage points (p.p.) for assets, 10.8 p.p. for sales, 9.2 p.p. for employment, 39.1 p.p. for intangible fixed assets, and 46.4 p.p. for tangible fixed assets. All these estimates are statistically significant at the 1% level. There is no evidence of a significant change in labour productivity (sales-to-employment cost ratio), over the 3-year time horizon.

The treatment effect is generally larger for younger companies and for companies with a larger proportion of intangible fixed assets. The results are robust to changes in the matching method, the inclusion of additional controls, adjustment for inflation, and controlling (in a panel setting) for unobserved time-invariant differences between treated and control-group companies. The results remain consistent when we examine an alternative sample of countries—Greece, Romania, and Spain—where data on the number of employees, rather than employment costs, is widely available.

In terms of survival, beneficiaries are 2.8 p.p. less likely than matched companies to go bankrupt by the end of 2023. We find a more positive effect on survival for smaller and older companies.

These results confirm that guaranteed loans are associated with substantial growth among beneficiaries, aligning with COSME's objective of improving access to finance to SMEs that would otherwise face credit constrains. From a policy perspective, it is also important to point out that guaranteed loans do not cause unwanted effects, like a drop in long-term labour productivity or an increase in failure rate.

Table of Contents

1 Introduction

EU SME guarantees, funded by the European Union (via the European Commission) are important policy tools to support SMEs. The COSME Loan Guarantee Facility (LGF) is the latest of a series of EU-level loan guarantee programs implemented by the EIF. The series includes:

- "SMEG 1998", SME guarantee facility (under the Growth and Employment Initiative, 1998–2000),
- "MAP" guarantee facility (under the Multi-Annual Programme (MAP) for Enterprises and Entrepreneurship for SMEs, 2001–2006),
- "CIP " guarantee facility (under the Competitiveness and Innovation Framework Programme, 2007–2013), and
- “COSME” loan guarantee facility (under the EU Programme for the Competitiveness of Enterprises and Small and Medium-sized Enterprises, 2014–2020).

These initiatives have been successfully deployed and have since been succeeded by the ongoing “InvestEU” programme (2021–2027).

Through these programs, the EIF offers guarantees and counter-guarantees to selected financial intermediaries to help them provide more credit to SMEs. The policy aims to reduce SMEs' financial constraints, allowing them to pursue investment opportunities they could not finance otherwise. In this report, we present the results of the analysis of the treatment effect of the COSME loan guarantee facility (LGF) in four European countries (Greece, Poland, Romania, and Spain) during 2015-2023.

Several studies have explored EIF-backed guaranteed loan programs. Asdrubali and Signore (2015) estimate the economic impact of the MAP guarantee facility in Central, Eastern and South-Eastern European (CESEE) Countries in the period 2005-2012. The analysis combines propensity scores and difference-in-difference estimation to evaluate the effect of having received a MAP-guaranteed SME loan on firm performance (employment, production, profitability and total factor productivity) against a control group of comparable firms. The authors find that 5 years after the issuance of the guaranteed loan, and compared to matched companies, beneficiaries increased their sales by an additional 19.6%, workforce by 17.3%, and had a temporary setback in productivity. Micro and young SMEs have benefited the most from MAP-guaranteed loans in terms of economic additionality.

Using a similar methodology, Bertoni et al. (2023) looked at MAP and CIP beneficiaries in France in the period 2002-2015. The authors find that, over a 5-year horizon, and – again – compared to matched companies, sales increase in logarithms by 0.0656 (6.8 percentage points), employment cost by 0.0689 (7.1 p.p.), and assets by 0.0672 (7.0 p.p.). The authors find that it takes at least 3 years for the treatment effect to be fully visible and that beneficiaries are still significantly larger than matched companies 10 years after the loan signature.

Bertoni et al. (2019) investigated MAP and CIP guaranteed loans in Italy, Benelux and Nordic countries (Denmark, Finland, Norway and Sweden) from 2002 to 2016. The authors find that over the three years after the beginning of the signature year, beneficiaries grew more than matched companies in terms of sales (14.8 p.p.), employment (16.9 p.p.), assets (19.6 p.p.), and share of intangible assets (1 p.p.).

Brault and Signore (2019) provide a pan-European assessment of EU MAP and CIP programs from 2002 to 2016. They found that guaranteed loans positively affect the growth of firms' assets (by 7 to more than 35 p.p.), the share of intangible assets (by one third of the initial share in Italy and the Nordic countries), sales (by 6 to 35 p.p.), and employment (by 8 to 30 p.p.).

These studies (e.g., Bertoni et al. 2019, 2023; Brault and Signore, 2019) also find that beneficiaries have lower bankruptcy rates compared to matched firms.

The key contribution of the present study is to extend these findings to a different EIF guarantee programme (COSME LGF), to a more recent period (2015-2023), and to focus on four countries that are among the least studied in this literature (Greece, Poland, Romania, and Spain).

Similarly to previous programs, COSME guarantees target SMEs, which experience well-known difficulties in accessing credit[2] because of the high information opacity, low value of their collateral, weak financial ratios, and high sales and profit volatility (Berger and Udell, 1998). Therefore, we expect the companies receiving COSME guaranteed loans to benefit from the improved access to finance, with positive consequences in terms of growth, investments, labour productivity, and survival.

The benefits of COSME guarantees might vary across categories of companies and be particularly beneficial for younger, smaller companies, with less tangible assets, plagued by stronger information asymmetries and with lower values of collateral. Further differences might be at play across industries, signature years, and countries.

While all COSME products are targeted to SMEs, in a few cases the target groups are the riskiest subsets of SMEs, including start-ups or SMEs with weak credit scores. For the latter, the presence of EIF guarantees is particularly crucial to secure loans, and the benefits of these loans should be stronger.

COSME guarantees are provided to companies in each country by selected financial intermediaries, typically a mix between commercial banks and National promotional institutions and other types of guarantee institutions. EIF signs a specific contract with each local financial intermediary. Among others, the contracts define the characteristics of the EU guarantee including the total volume, which is made available to the financial intermediary, to be used over a period of 2 to 3 years typically.

EIF and the financial intermediaries also agree on the characteristics of the loans, including the purpose of the loans (e.g., financing working capital or long-term investments), the maturity (short or long term), the guaranteed rate or the loan-to-value ratio, or the presence of counter-guarantees and the target group of SMEs. Such characteristics are specified in the individual guarantee agreements as contractual eligibility criteria. The effectiveness of COSME guarantees could vary across these characteristics. Most notably, guarantees meant to finance long-term investments are

[2] As the legal base for the programme recites, COSME aims at reducing “the particular difficulties that viable SMEs face in accessing finance, either due to their perceived high risk or their lack of sufficient available collateral”. Regulation (EU) No 1287/2013 establishing a Programme for the Competitiveness of Enterprises and Small and Medium-sized Enterprises (COSME) (2014–2020). OJ L 347, 20.12.2013, pp. 33–49.

expected to favor companies' growth in tangible and intangible assets. Instead, guarantees targeting working capital needs might boost short-term expenses, including employment costs. Interestingly, some of the COSME products were particularly focused on alleviating the consequences of the COVID-19 pandemic on beneficiaries’ working capital.

COSME guaranteed loans often provide companies with the additional benefit of reducing or even eliminating collateral requirements. In this way, they particularly benefit younger firms with low asset tangibility, facilitating their access to capital despite lack of collateral.

Our main findings confirm the positive impact of COSME guaranteed loans. Beneficiaries outgrow matched companies three years after the beginning of the signature year. The additional logarithmic growth is 0.125 (13.3 p.p.) in assets, 0.103 (10.8 p.p.) in sales, 0.088 (9.2 p.p.) in employment, 0.330 (39.1 p.p.) in intangible fixed assets, and 0.381 (46.4 p.p.) in tangible fixed assets. All these estimates are statistically significant at the 1% level. There is no evidence of a significant change in labour productivity over the 3-year time horizon. However, we find a temporary setback in labour productivity over the signature year, offset by a labour productivity increase in the following year. The treatment effect is generally larger for younger companies and for companies with a larger proportion of intangible fixed assets. The results are robust to changes in the matching method, the inclusion of additional controls, adjustment for inflation, and controlling (in a panel setting) for unobserved time-invariant differences between treated and control-group companies. In terms of survival, beneficiaries are 2.8 p.p. less likely than matched companies to go bankrupt by the end of 2023. We find a more positive effect on survival for smaller and older companies.

Because of data availability, in our main analysis we focus on three of the four countries: Poland, Romania, and Spain. Because data on employment cost is rarely available for companies in Greece, we analyse this country separately, using an alternative variable to capture employment: number of employees. However, this variable is seldom available for Poland, leading to its exclusion this additional analysis. Results are consistent once we examine the alternative sample of countries (Greece, Romania, and Spain).

Overall, these results confirm that guaranteed loans are associated with substantial additional growth for the beneficiaries, which also leads them to invest significantly more in tangible and, more interestingly, intangible fixed assets. This latter result is relatively rare in the related literature. It is possibly due to the specific nature of the guaranteed loans in our sample, some of which – as discussed above – target transactions without collateral, which are particularly appropriate for investments in intangible fixed assets.

From a policy perspective, it is also important to point out that guaranteed loans do not cause unwanted effects, like a drop in long-term productivity or an increase in failure rate.

The rest of this report is organized as follows: in section 2 , we present the methodology we used for the analysis. In section 3 , we discuss the sample construction. In section 4 , we illustrate the results of the analysis. In section 5 , we summarize the main findings and draw conclusions.

2 Methods

2.1 Variables of interest

We evaluated the treatment effect of guaranteed loans on several high-level dimensions and the related KPIs of firm performance. Namely:

- Economic size growth (captured by the logarithmic growth of total assets; sales, employment, measured via the employment costs or, as second best, the number of employees -see discussion in section 0);
- Investments (captured by the logarithmic growth of tangible and intangible fixed assets);
- Labour productivity growth (measured as the ratio between sales and employment);
- Survival.

Growth estimates are based on accounting variables retrieved from Orbis for the period 2009-2023. We deflate all accounting variables using country and sector-specific producer price indices (at the level of NACE Rev. 2 divisions) with base year 2015, collected from the national statistical offices. All growth measures are winsorized at the 1% level to limit the impact of outliers. For survival, we used the information on the bankruptcy date of companies, extracted from Orbis[3].

2.2 Econometric approach

To establish a causal relationship between the receipt of a guaranteed loan and economic performance, one would ideally need to compare the outcome of companies that received the COSME-backed loans (“treated”) with the outcome of the same companies *had they not received the loan*. Absent information on what would have happened to the treated companies if they had not received the loan, we resort to a counterfactual analysis, in which the performance of treated companies is compared with the performance of companies that were virtually identical to the treated companies, but did not receive a COSME-backed loan, i.e., they were “untreated”. In section 3.4, we will explain the selection of such a counterfactual.

2.2.1 Growth models specifications

When analysing the growth measures (including changes in labour productivity), we adopt the difference-in-difference (diff-in-diff) approach to evaluate the impact of guaranteed loans on treated companies. This approach is applicable when information on the outcome before the treatment is available to researchers. The idea of diff-in-diff is to compute the outcome difference of treated and controls after the treatment and subtract the outcome difference that had been there already before the treatment had any effect (conditional on a given value of controls). The diff-in-diff methodology

[3] Bankruptcy date is the date in which the company status first changed to any of the below Orbis company statuses: Active (default of payment), Active (insolvency proceedings), Bankruptcy, Dissolved, Dissolved (bankruptcy), Dissolved (demerger), Dissolved (liquidation), Dissolved (merger or take-over), In liquidation, Inactive (no precision).

is based on a set of assumptions (for a full discussion, see for instance Lechner, 2010), among which the parallel trend assumption is particularly crucial. The assumption requires that if the treated had not been subjected to the treatment, they would have experienced the same trends as the untreated. Typically, this assumption is ensured by enforcing the parallel trend before the treatment.

In our case, we must make sure that treated and untreated observations have the same trends in terms of assets, sales, cost of employees, intangible and tangible fixed assets, before the treatment. We use both cross section and panel diff-in-diff specifications for our growth models.

In a cross-section setting, we use one observation for each treated and untreated company. We will analyse how companies grow between T-1 (the beginning of the signature year) and T+2 (the end of the second year after the signature year). For instance, for a company that received a guaranteed loan in June 2016, we will study its growth between Dec 31, 2015 to Dec 31, 2018. We decided to focus on this time horizon mainly because of data availability issues, discussed in section 0. In short, we can observe only a fraction of the treated companies over longer time horizons. As a result, our estimates are more precise (i.e., have more statistical power, see also discussion in section 3.3) over shorter time horizons.

Moreover, based on the previous literature we are confident that a 3-year horizon is appropriate to capture medium term treatment effects of guaranteed loans. This is also consistent with the average loan maturities in the observed sample (5 years for Spain and Greece, 4 years for Poland and 3 years for Romania). We use the following cross-section specification for our diff-in-diff growth model:

$$\mathit{\Delta}_3 Y_T = Y_{T+2} - Y_{T-1} = \beta_0 + \beta_1 Y_{T-1} + \beta_2 \mathit{\Delta}_1 Y_{T-1} + \beta_3 GLoan + \gamma X_{T-1} + \mu_T + s + c + \epsilon$$

Where $\mathit{\Delta}_3 Y_T = Y_{T+2} - Y_{T-1}$ represents the 3-year growth of the dependent variable (total assets, sales, cost of employment, intangible fixed assets, tangible fixed assets or labour productivity). *GLoan* is a dummy equal to 1 for treated observations and 0 otherwise. Its estimated coefficient compares the growth between treated and untreated companies over the same period, representing our diff-in-diff estimator.

The models control for companies' characteristics before the signature year (Y_{T-1}) and for their lagged growth ($\mathit{\Delta}_1 Y_{T-1} = Y_{T-1} - Y_{T-2}$). The former element allows to control for the level of the dependent variables, which in this study represent companies' size (e.g., total assets, sales, etc). Typically, growth rates are smaller for larger companies. The latter element is particularly important because it allows to control for any imbalance in the past growth trajectories between treated and untreated companies, and further ensures that the parallel trend assumption is verified.

Lastly, we control for other potentially relevant measures in T-1 (X_{T-1}). *Age* is the logarithm of the company's age in years. *Leverage* is computed as the ratio between the total liabilities[4] and total assets and captures the company's capital structure. *Cash_assets* is the ratio of cash and cash equivalents to total assets and captures the company's liquidity. Both factors can potentially correlate with a company's growth trajectory.

[4] Because total liabilities might be under-reported in Orbis, we measure it as total assets minus shareholders' funds.

Moreover, we control for signature year (μ_T), sector (s), and country (c) fixed effects. As shown in the following, we will conduct several robustness checks for our model specification, including considering different horizons for the treatment beyond T+2.

The most important robustness check is related to the use of a panel data model specification. In this case, we use all available observations for treated and untreated companies and estimate a two-way fixed effect panel data model, as follows:

$$\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 \Delta Y_{i,t-1} + \beta_3 GLoan_{i,t} + \gamma X_{i,t-1} + \mu_T + \omega_i + \epsilon$$

In this case, the dependent variables represent companies' annual growth in total assets, sales, employment cost, tangible and intangible assets and labour productivity. The two-way fixed effects models include company (ω_i) and time (μ_T) fixed effects. The step variable *GLoan* switches from 0 to 1 for treated companies in the year of the first treatment and is 0 for untreated companies. Its coefficient captures by how much treated companies' annual growth is higher than untreated companies' annual growth. It is our panel version estimate of the diff-in-diff treatment effect. We also control for past size, size growth rate, age, leverage, and liquidity.

2.2.2 Survival analysis

Our last dependent variable is the companies' survival. Again, we adopt a counterfactual approach, although the control group is slightly different, as explained in section 0. We adopt two alternative specifications to model the survival of treated and untreated companies. First, we simply test whether treated companies are more or less likely than untreated companies to fail up to 2023, when EIF retrieved the survival information. Our dependent variable is a dummy equal to 1 for failed companies and equal to 0 for the others. We use probit models in which regressors are the same as the ones used in the cross-section growth models. The coefficient of the GLoan dummy will capture differences in the failure likelihood across treated and untread companies.

Second, we exploit the information on when the company failed. We use a Cox (1972) survival analysis in which the dependent variable is the hazard ratio of failing, i.e., the probability of failing for a given exposure time, conditional of not having failed till that moment. The exposure time is the number of years since the signature year and 2023 or, if the company failed before, till the year of failure. The Cox is more precise than the probit because it models the timing of the event, not only its likelihood. Specifically, it allows to account for the fact that companies that received loans in earlier years were exposed to the risk of failing for longer than others. Regressors are identical to the probit specification, and again the coefficient of *GLoan* will capture differences in the hazard rates of failing across treated and untread companies.

3 Data

3.1 Population of treated companies

In this study, the population of interest consists in all companies that received a COSME-guaranteed loans in the period 2015-2023, in Greece, Poland, Romania, or Spain. The data, as fetched by the EIF in January 2024, consists of 325,410 loans granted to 285,419 SMEs. Companies might receive more than one COSME guaranteed loan during this period and even more than one loan per year. As performance is measured using accounting data, which naturally has annual frequency, the unit of analysis is not the individual loan but the company-signature year, i.e., every year in which a company receives at least one guaranteed loan from COSME. For simplicity, in the following we refer to these units as simply “guaranteed loans”, “loans”, “treated observations” or “treated companies”.

Table 1 shows the distribution of the population by country and signature year. Most loans (63.42%) were granted to Spanish companies, with a fairly even distribution across years, except for an increased activity in 2020. COSME loans were granted to Polish firms only since 2016, with a peak around 2019. Greek loans, representing 8.22% of the population, were granted between 2016 and 2022 and more frequently in 2021. Lastly, Romania accounts for 4.84% of loans, with most issued between 2017 and 2021 and a peak of activity in 2019.

Table 1 – Descriptives of the distribution of the population of loans (company-signature year) by country and signature year

	Greece		Poland		Romania		Spain		Total	
	N	Col%	N	Col%	N	Col%	N	Col%	N	Col%
2015	0	0.00	0	0.00	193	1.23	19,463	9.43	19,656	6.04
2016	321	1.20	3,332	4.35	518	3.29	21,744	10.54	25,915	7.96
2017	2,950	11.02	4,118	5.38	1,975	12.55	26,887	13.03	35,930	11.04
2018	4,771	17.83	9,389	12.27	1,750	11.12	27,380	13.27	43,290	13.30
2019	5,655	21.13	19,314	25.24	4,558	28.96	24,574	11.91	54,101	16.63
2020	3,922	14.66	13,533	17.68	1,874	11.91	34,752	16.84	54,081	16.62
2021	9,040	33.78	13,642	17.82	3,259	20.70	21,192	10.27	47,133	14.48
2022	99	0.37	7,549	9.86	651	4.14	21,913	10.62	30,212	9.28
2023	0	0.00	5,659	7.39	963	6.12	8,470	4.10	15,092	4.64
Total	**26,758**	**100**	**76,536**	**100**	**15,741**	**100**	**206,375**	**100**	**325,410**	**100**

3.2 Sample construction

Since accounting data are not available for all firms and years, the econometric study is conducted on a sample of firms, rather than on the whole population described in the previous section. Ideally, the final sample should be sufficiently large and randomly extracted from the population.

Accounting data were retrieved from the Bureau Van Dijk's Orbis database. As a first step, the EIF matched all beneficiaries with Orbis to identify a Bureau Van Dijk (BvD) ID code, based on the beneficiaries' names, city and country. Overall, only 116,205 loans, corresponding to 35.71% of the original population have a BvD ID code. We excluded the remaining loans from any further analysis.

Column II of Table 2 shows the distribution of loans with a BvD ID code by country and year. The coverage of Greece was especially low (21.55%), and we tried to boost it by performing another round of matching with Orbis based on the companies' names and country, only. This increased the coverage of Greek companies to 34.09%. Orbis coverage of COSME beneficiaries is particularly high for Romania (73.56%). In Poland and Spain, 38.78% and 31.89% of loans could be associated with a BvD ID code, respectively. In terms of signature years, the coverage is 30.34% for loans granted in 2015 and progressively increases to 51.19% for loans granted in 2020. The coverage is much lower for recently granted loans and is as low as 4.31% for 2023 loans.

Our sample is further restricted because of the availability of accounting data in Orbis. In fact, Orbis does not report accounting data for all companies included in it. In other words, we were forced to exclude many loans associated with a BvD ID because we could not retrieve accounting information on the beneficiary firm. For our growth estimates, we need both information before the treatment (T-1) and after (T+t, with different values of t).

Therefore, we analyse the available accounting information for each of the most important variables of interest in our study around the treatment year in Figure 1. In the year before the signature year and in the signature year itself, accounting data on the beneficiaries' total assets, sales, cost of employees and tangible and intangible fixed assets, were available for around half of the loans associated with a BvD ID code. For total assets, we have 61,032 suitable data points in T-1 and 62,732 data points in T. The incidence of missing information increases as we move forward in time from the signature year, and is as low as 26% in T+5. For other variables, the incidence of missing values is generally higher. Notably, the cost of employment is systematically missing in Greece.

In Figure 2, we focus on total assets and analyse data availability by country in both year T-1 and in year T+t, with t=0…5. Romania is the country with more available data with respect to the population, while Poland and Greece are the least well covered. Overall, these Figures suggest that assessing the impact of loan guarantees beyond T+2 is challenging because of the lack of recent accounting data. For this reason, in agreement with the EIF, we decided to focus most of our attention on the T+2 horizon in our impact assessment exercise.

In preparation for the following steps, we decided to first exclude companies without total assets in T-1. At this stage we also include further minor data refinements and excluded:

- Companies with total assets exceeding 42 million EUR in T-1 (as they likely did not meet the European Commission's SME definition when they received the loan[5]);
- Companies with negative values of total assets in T-1;
- Loans granted since 2021, because of the almost systematic unavailability of data in the post treatment period for these loans;
- Companies treated in the foundation year (213 cases), because of the unreliability of accounting data in these cases;
- Companies without industry NACE codes in Orbis.

These exclusions result in a sample of 52,873 loans, corresponding to 16.25% of the original population and described in Column III of Table 2. We used this sample for the extraction grid described in section 3.4.1 .

Second, we exclude companies without a full set of accounting measures in T-1. Besides total assets, we also require the availability of sales, cost of employees, tangible and intangible fixed assets, equity value ("shareholder funds" in Orbis), cash and cash equivalents. We used the latter two measures to compute control variables for leverage and liquidity. We used the resulting sample of 35,464 loans (10.90% of the original population) in the survival analysis described in section 4.2. We report the distribution of this sample by country and signature year in Column IV of Table 2.

To carry out our growth estimates, we exclude companies without a full set of accounting measures in T+2. In this case, we require information on the variables we use as key performance indicators, i.e., total assets, sales, cost of employees and tangible and intangible fixed assets in T+2. The resulting sample of 21,034 (6.4% of the original population) is used in the Propensity Score Matching described in section 3.4.2 , and in the growth analyses (section 4.1). We report the distribution of this sample by country and signature year in Column V of Table 2.

As mentioned, Orbis does not report the cost of employees of Greek companies, and this causes their exclusion from the sample described in Columns IV and V of Table 2. Employment is better measured using the cost of employment than number of employees in our setting. The number of employees is a data field in Orbis that has relatively poor quality and is not regularly updated, especially for SMEs. Employment cost also captures changes in full-time equivalent terms beyond what would be possible from a simple headcount. For this reason, we run most of our analyses in the sample selected based on the availability of cost of employment. However, to make sure that Greece is included in our exercise, we generate an alternative sample in which we require the availability of information on number of employees rather than cost of employment. The sample is described in column VI of Table 2 and used in section 4.1.4 .

[5] While this is a rough indicator of SME status and not a substitute for a thorough SME eligibility assessment, this exclusion aims to reduce heterogeneity in the sample and thus facilitate the identification of the control group as well as to improve its quality.

Table 2 – Sampling from the population of guaranteed loans (company-signature year)

	I	II		III		IV		V		VI	
	Total	With BvD ID code		With total assets in T-1		With complete info (and cost of employment) in T-1		With complete info (incl. cost of employment) in T-1 and T+2		With complete info (incl. no. of employees) in T-1 and T+2	
	N	N	%	N	%	N	%	N	%	N	%
Total	**325,410**	**116,205**	**35.71%**	**52,873**	**16.25%**	**35,464**	**10.90%**	**21,034**	**6.46%**	**19,943**	**6.13%**
Greece	26,758	9,122	34.09%	1,548	5.79%	0	0.00%	0	0.00%	1,005	3.76%
Poland	76,536	29,681	38.78%	5,486	7.17%	2,058	2.69%	1,157	1.51%	465	0.61%
Romania	15,741	11,579	73.56%	7,244	46.02%	6,060	38.50%	4,680	29.73%	4,759	30.23%
Spain	206,375	65,823	31.89%	38,595	18.70%	27,346	13.25%	15,197	7.36%	13,714	6.65%
2015	19,656	5,963	30.34%	3,143	15.99%	2,003	10.19%	1,695	8.62%	1,474	7.50%
2016	25,915	10,374	40.03%	4,853	18.73%	3,309	12.77%	2,810	10.84%	2,466	9.52%
2017	35,930	16,166	44.99%	8,902	24.78%	6,286	17.50%	5,509	15.33%	5,250	14.61%
2018	43,290	18,691	43.18%	9,067	20.94%	6,138	14.18%	5,334	12.32%	5,263	12.16%
2019	54,101	27,644	51.10%	11,352	20.98%	6,671	12.33%	5,587	10.33%	5,409	10.00%
2020	54,081	27,682	51.19%	15,556	28.76%	11,057	20.45%	88	0.16%	81	0.15%
2021	47,133	6,641	14.09%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2022	30,212	2,607	8.63%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2023	15,092	651	4.31%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Figure 1 – Data availability on key performance indicators by time since signature year

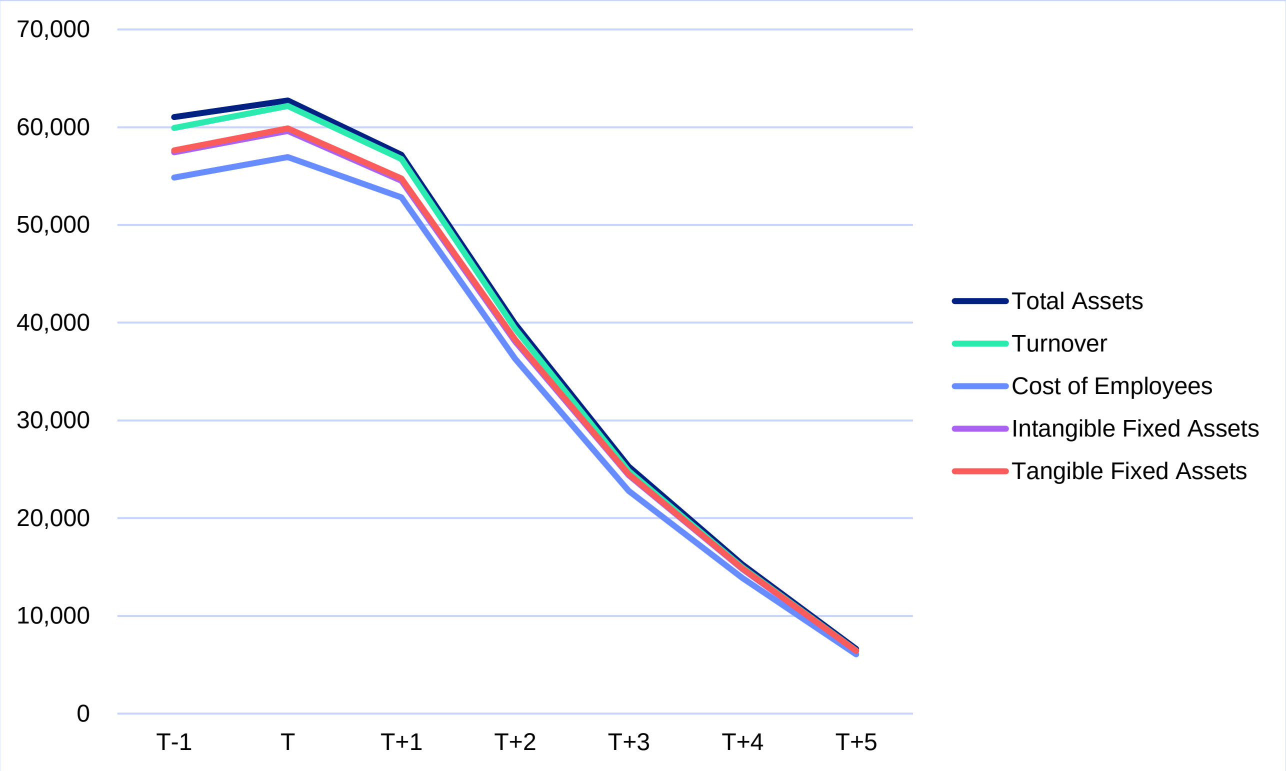
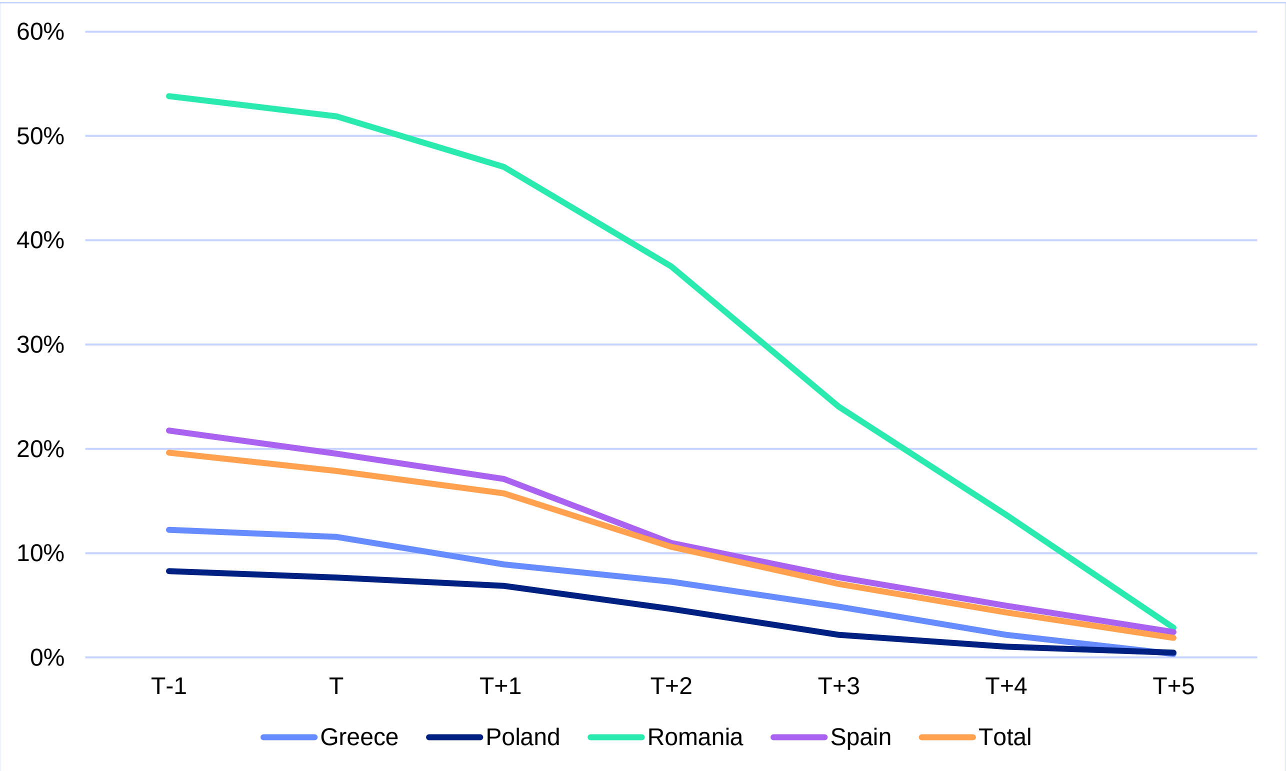


Figure 2 – Data availability on total assets by country and time since signature year



3.3 Power analysis

Before identifying the control group, we conduct a power analysis to determine the necessary sample size to study the phenomenon. The objective is not to perform a full-fledged power simulation but rather to identify the order of magnitude of the sample size that we need to reasonably identify the effect of guaranteed loans.

In this report we look at the treatment effect of guaranteed loans over different periods (1-5 years) and dependent variables (total assets, sales, employment, intangible fixed assets, tangible fixed assets, and labour productivity) and using several methods (different versions of PSM and panel data models). Performing a separate power analysis for each possible combination of period, dependent variable and method would result in a complex exercise. Considering that the aim of this section is to give a ballpark estimate of the sample size needed to study the phenomenon, we instead conduct the power analysis on what we consider a representative setting: the cross-sectional estimate of the treatment effect of guaranteed loans on firm's sales with a 1-year time horizon and using 1:1 PSM.

The power analysis studies the relationship between 1. the power of a test ($1-\beta$), 2. the sample size (N), 3. the level of significance (α) and 4. the non-centrality parameter (δ, which is the extent to which the null hypothesis is false). Here we want to calculate the sample size N given the other parameters.

To set δ, we start from estimates presented in a recent work by Bertoni et al. (2023). The 1-year logarithmic growth in sales in their sample of French guaranteed-loan beneficiaries is 0.064, which exceeds the 0.027 for control group companies. The difference of 0.036 (with a standard deviation of 0.20) is their estimate of treatment effect and our starting point for δ. If we set power at $1-\beta=90\%$ and significance $\alpha=1\%$, standard power calculation leads us to a sample size of 1,858 units, which (because of 1:1 PSM) means 929 treated companies. In other words, if the true treatment effect in this study were of similar size as the one estimated in Bertoni et al. (2023), a sample of 929 beneficiaries would give us a 90% probability of rejecting the false null hypothesis that treatment effect is 0 while maintaining type-I error at 1%.

Note that this number is much smaller than the total number of "usable" observations from Table 2. Moreover, both in the main and alternative analyses, we would still have sufficient power to run the analysis even if we split the sample by country or by year, except for 2020, for which we have very few available observations in T+2 as of the time of the study.

Of course, as illustrated in Table 3, the required sample size will increase if the true treatment effect is smaller, if we want greater power, or if the significance level is smaller. A δ that is 0.75x that found in Bertoni et al. (2023), will require a sample of 3,298 companies (of which 1,649 treated) to maintain a power of 90% with a 1% significance. The sample size would grow to 7,416 (of which 3,708 treated) if the treatment effect were half of the value estimated by Bertoni et al. (2023). A more conservative significance level of 0.1% would require a sample of 2,610 companies (1,305 treated) to achieve the same performance. All these sample sizes are comfortably within the range of total observations in Table 2.

Table 3 – Power analysis

Scenario	Significance (α)	Power (1-β)	Non-centre (δ)	N. total	N. treated
Base	0.01	0.90	0.03656	1,858	929
Power 95%	0.01	0.95	0.03656	2,222	1,111
Alpha 0.1%	0.001	0.90	0.03656	2,610	1,305
Delta 0.75x	0.01	0.90	0.02742	3,298	1,649
Delta 0.50x	0.01	0.90	0.01828	7,416	3,708

3.4 Identification of control group

As explained in section 2.2, we compared the performance of companies that received a guaranteed loan (the treated companies) with those that had similar ex-ante characteristics but did not receive a guaranteed loan. We refer to these companies as the "control group" of untreated companies. We identified control group companies from Orbis.

Orbis contains information on millions of companies. Downloading the universe of companies operating in the four countries of interest would be impractical. Therefore, we proceeded in two sequential steps, as follows:

1. *Extraction grid*: The identification of potential control group companies, which presented characteristics similar to those of the treated companies in terms of country, age classes, and industry, in each signature year.
2. *Propensity Score Matching*: The identification of a more refined control group, which is similar to the treatment group in terms of its propensity score (i.e., the probability of receiving the treatment).

3.4.1 Extraction grid

We focused on loans granted to companies for which we have information on total assets in year T-1 and any of the following three years, with less than or equal to 43 million EUR of total assets in T-1 and with NACE and foundation year information, in the 2015-2021 period (see again Column III of Table 2).

We downloaded from Orbis a potential control group of companies with similar distributions along countries, age classes, industries, and signature years to the treated companies at the time of the treatment. To do so, we developed an extraction grid that includes the number of treated companies that present homogeneous characteristics in each stratum, i.e., a combination of countries, age classes, industries, and signature years.

For age classes, we combined information on the foundation year of treated companies from EIF and Orbis, taking the minimum of the two[6]. We computed companies' age at the time of the treatment and then classified treated observations in five groups:

[6] In the few (5) cases in which companies received a loan before the foundation year, we set the foundation year equal to the signature year. There are 11 companies for which the signature year is equal to the foundation year (i.e., they received a loan at foundation), and total assets is available in T-1. We fixed this likely mistake in the data and set their foundation year back by 1 additional year in these cases.

- 1 year old,
- 2-4 years old,
- 5-9 years old,
- 10-19 years old, and
- more than 19 years old.

For industries, we adopted a classification based on NACE codes and, in particular, NACE Rev. 2 two-digit divisions:

- Agriculture and Mining: NACE sections A and B (codes 01-09),
- High and Medium Tech Manufacturing: a subset of NACE section C according to the European Commission classification of high and medium tech manufacturing (20-30, 33),
- Low Tech Manufacturing: a subset of NACE section C, with the remaining NACE 2 digits (10-19, 31-32),
- Construction: NACE section F (codes 41-43),
- Trade: NACE section G (codes 45-47),
- Knowledge Intensive services according to the European Commission definition (codes 50 - 51, 58 - 66, 69 - 75, 78, 84-88, 90-93),
- Other services: all remaining services (codes: 35-39, 49, 52-56, 68, 77, 79-82, 94-99).

For signature years, we focused only on the period 2015-2020, due to the very low availability of data in more recent years.

Considering these characteristics, the number of strata is equal to four (countries) times six (signature years) times five (age classes) times seven (industries), for a total of 840. The treated companies populate only 736 of these 840 strata, as some combinations are never found in the data. We produced an extraction grid including the number of loans in each of these strata.

The EIF used the extraction grid to download from Orbis a number of company-year observations extracted randomly and equal to up to 40 times the number of loans in each stratum (depending on data availability in Orbis). To ensure that the extracted data would be useful, further selection criteria for the untreated observations were included, i.e., 1. total asset was available in T-1 and 2. total asset was lower than 43 million EUR.[7] In total, 1,980,670 company-year observations were downloaded in this way, corresponding to the potential control group. In Table 4, we present the distribution of the loans with available total assets in T-1 and the potential control group by signature year, age classes, country, and industry classes used in the extraction grid. The ratio of potential control group companies to treated observations is, on average, 36.5. It is worth noticing that both the treated sample and the potential control group have the same unit of analysis at the company-year level.

Potential control group companies do not necessarily have the same characteristics as the treated companies, yet. In fact, chi2 tests revealed that the distributions across categorical variables are significantly different across treated and potential control group companies.

[7] The reader should notice that the extraction grid is virtually identical to a Coarsened Exact Matching, where matching variables are used to define the strata. The only difference is that we did not use matching weights.

Table 4 – Distribution of treated observations and potential control group observations

	Treated (T) with available total assets in T-1	Potential control group (PCG) with available total assets in T-1	Total (T+PCG)	PCG/T
Signature year				
2015	3,143	117,110	120,253	37.3
2016	4,853	181,206	186,059	37.3
2017	8,902	335,189	344,091	37.7
2018	9,067	335,263	344,330	37.0
2019	11,352	417,935	429,287	36.8
2020	15,556	543,967	559,523	35.0
Age classes				
1	3,285	110,216	113,501	33.6
2-4	10,715	379,519	390,234	35.4
5-9	11,513	419,590	431,103	36.4
10-19	15,066	560,521	575,587	37.2
20-197	12,294	460,824	473,118	37.5
Country				
Greece	1,548	54,402	55,950	35.1
Poland	5,486	201,687	207,173	36.8
Romania	7,244	276,684	283,928	38.2
Spain	38,595	1,397,897	1,436,492	36.2
Industry				
AB	2,317	90,472	92,789	39.0
CHT	4,266	154,354	158,620	36.2
CLT	4,211	151,341	155,552	35.9
F	6,549	240,651	247,200	36.7
G	14,772	536,404	551,176	36.3
KI services	8,689	323,667	332,356	37.3
Other services	12,069	433,781	445,850	35.9
Total	**52,873**	**1,930,670**	**1,983,543**	**36.5**

We further analyse the summary statistics of our variables of interest in T-1 for both treated and potential control group companies in Table 5.

We find that untreated companies in the potential control group tend to be older, smaller, have slower growth rates (for assets, sales, employment cost, tangible and intangible fixed assets), lower labour productivity, higher leverage and cash ratio. All the differences are statistically significant at the 1% level (t-tests).

Table 5 – Summary statistics of variables of interest in T-1 for treated observations and potential control group observations

	All companies	Potential control group (PCG) with available total assets in T-1	Treated (T) with available total assets in T-1	Difference T-PCG	t-test significance
Ln(Total assets$_{T-1}$)	11.893	11.875	12.573	0.698	***
ΔLn(Total assets$_{T-1}$)	0.078	0.074	0.205	0.131	***
Ln(Sales$_{T-1}$)	11.574	11.535	12.851	1.316	***
ΔLn(Sales$_{T-1}$)	0.048	0.043	0.205	0.161	***
Ln(Emp. cost$_{T-1}$)	10.895	10.878	11.344	0.465	***
ΔLn(Emp. cost$_{T-1}$)	0.101	0.097	0.206	0.109	***
Ln(Int. assets$_{T-1}$)	1.857	1.824	2.992	1.168	***
ΔLn(Int. assets$_{T-1}$)	0.010	0.007	0.132	0.125	***
Ln(Tang. assets$_{T-1}$)	8.769	8.721	10.413	1.692	***
ΔLn(Tang. assets$_{T-1}$)	0.067	0.061	0.272	0.211	***
ΔProductivity$_{T-1}$	9.206	9.183	9.839	0.657	***
Leverage $_{T-1}$	1.104	1.113	0.776	-0.337	***
Cash ratio $_{T-1}$	0.224	0.226	0.152	-0.074	***

3.4.2 Propensity Score Matching

An ideal control group for this study does not present differences with respect to the treated sample in the distribution along countries, industries, signature years and age classes, nor in the mean values of the variable of interest computed in T-1.

To extract such ideal control group from the potential control group companies, we performed a Propensity Score Matching (PSM), in the spirit of Asdrubali and Signore (2015) and Bertoni et al. (2019).

PSM is quite a standard matching method in the literature, especially in combination with the diff-in-diff methodology (e.g., Blundell et al., 2004; Heckman et al., 1997). When PSM is applied to a potential control group of companies identified with the extraction grid described above, it is confirmed that there is common support, i.e., that observations with a given set of characteristics exist both in the treatment and control group.

We tried several alternative specifications for the PSM (including matching separately for each outcome variable, similar to Bertoni et al., 2023) and eventually selected the matching algorithm with the best balance after matching.

Specifically, we run separate PSM for each country and each signature year, accounting for the cross-country and cross-time possible variations in the allocation criteria of guaranteed loans to beneficiaries. In each subsample defined within a country and a signature year, we first run a probit model with treated and potential control group companies in which the dependent variable is 1 for the former companies. The choice of the PSM variables is guided by the extant literature on the assignment mechanism of bank loans, as in e.g. Kremp and Sevestre (2013), Asdrubali and Signore (2015) and Bertoni et al. (2019). In addition, this study also includes growth rates in the PSM model, which is also an important determinant of loan allocation (sales growth), see e.g. Sinnott et al. (2023). The matching variables include:

- Total assets, sales, employment cost, tangible and intangible fixed assets in T-1, taken in logarithms;
- Labour productivity in T-1, captured by sales divided by employment cost and winsorized at the 1% level;
- The logarithmic growth of total assets, sales, employment cost, tangible and intangible fixed assets between T-2 and T-1, winsorized at the 1% level to reduce the impact of outliers;
- Leverage (computed as the ratio of liabilities on assets) and cash ratio (computed as the ratio of cash and cash equivalent on assets) in T-1;
- The logarithm of companies' age;
- NACE 2-digit codes.

Matching on both levels and growth of the variables of interest ensures not only that selected untreated companies are similar to treated ones in T-1, but also that they were on the same growth trajectory, which is an essential assumption of the diff-in-diff methodology (the parallel trend assumption discussed in Methods). The drawback of this choice is that very young companies, for which information in T-2 is simply not defined, are systematically excluded from the analysis.[8]

The choice of the matching variables ensures that all matched treated and untread observations have no missing values of the variables of interest in T-1. As such, we could use the same control group for all the subsequent growth analyses. Moreover, we decided to exclude from the analysis both treated and untread observations that would not be included in the final estimates, i.e., those for which data on assets, sales, employment cost, and tangible and intangible fixed assets were not available in T+2. We describe the final sample of treated companies in column V of Table 2.[9]

After running each probit model, we estimated the propensity scores and selected the nearest neighbour of treated companies among untreated companies.

We then tested the balancing of our matching along all matching variables. We show results in Table 6. For each variable, we observe a substantial drop in the bias between treated and control companies after matching. T-tests confirm that none of the variables are significantly different across the two groups after matching.

The EIF provided us with a panel dataset of accounting variables for the treated and matched control group from 2009 to 2023, which we used in the econometric analyses.

[8] Companies 2 years old or younger at the time of the treatment represent 35.3% of the initial population of COSME company-year loans, 19.54% of the loans associated with a BvD ID code, and 13.20% of the loans with available information on total assets in T-1.
[9] When analysing survival, we resorted to a different matching algorithm that does not require the availability of accounting measures after treatment.

Table 6 – PSM diagnostics and descriptives

	Before matching			After matching			Bias reduction
	Treated	Control	Delta	Treated	Control	Delta	
ΔLn(Total assets$_{T-1}$)	0.20	0.12	0.079	0.18	0.17	0.003	95.8%
ΔLn(Sales$_{T-1}$)	0.21	0.14	0.070	0.19	0.18	0.005	92.5%
ΔLn(Emp. cost$_{T-1}$)	0.21	0.15	0.065	0.21	0.21	0.001	99.1%
ΔLn(Int. assets$_{T-1}$)	0.12	0.06	0.062	0.11	0.12	-0.003	94.4%
ΔLn(Tang. assets$_{T-1}$)	0.30	0.18	0.125	0.27	0.27	0.002	98.2%
Ln(Total assets$_{T-1}$)	12.70	12.79	-0.086	12.87	12.84	0.027	68.2%
Ln(Sales$_{T-1}$)	13.00	12.97	0.033	13.19	13.17	0.018	45.9%
Ln(Emp. cost$_{T-1}$)	11.32	11.39	-0.069	11.48	11.47	0.006	90.9%
Ln(Int. assets$_{T-1}$)	2.88	2.48	0.395	3.03	3.02	0.002	99.4%
Ln(Tang. assets$_{T-1}$)	10.58	10.38	0.204	10.85	10.81	0.036	82.3%
Productivity$_{T-1}$	9.85	8.75	1.106	9.48	9.50	-0.019	98.3%
Leverage$_{T-1}$	0.76	0.75	0.012	0.73	0.74	-0.007	39.4%
Cash ratio$_{T-1}$	0.13	0.18	-0.051	0.12	0.12	-0.002	96.8%

4 Results

4.1 Growth

4.1.1 Baseline results

Table 7 reports the results of the diff-in-diff estimation of the average treatment effect of guaranteed loans on 3-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity.

The regression results indicate that guaranteed-loan beneficiaries grow significantly (p-value<1%) more than matched companies in terms of total assets, sales, employment cost, intangible fixed assets, and tangible fixed assets. Results relating to labour productivity growth are not significant. In terms of magnitude, 3-year logarithmic growth of total assets is 0.125 (i.e., +13.3 p.p., computed as exp(0.125)-1) higher in beneficiaries than matched companies. In terms of comparison, this is slightly higher than the 0.0893 Bertoni et al. (2023) found for guaranteed loans in France. Over the same time window, the treatment effect on logarithmic sales growth is 0.103 (+10.8 p.p.), which again is slightly higher than the 0.0625 in Bertoni et al. (2023). The 3-year treatment effect on growth in employment cost is 0.088 (9.2 p.p.), compared to 0.069 in Bertoni et al. (2023).

Looking at fixed assets, rather than total assets, we find a very substantial increase in intangible fixed assets, which increase by 0.330 (+39.1 p.p.), and tangible fixed assets, which increase by 0.381 (+46.4 p.p.). In other words, the treatment effect on tangible and intangible fixed assets outpaces that of total assets and, as a consequence, that of current assets. The loan provides liquidity which beneficiary firms progressively turn into fixed assets, tangible or intangible.

Finally, the analysis cannot reject the null hypothesis that there is no gain (or loss) in labour productivity on average for beneficiaries.

Table 7 – Baseline diff-in-diff regression results

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.125***	0.103***	0.088***	0.330***	0.381***	0.183
	(0.005)	(0.007)	(0.006)	(0.027)	(0.017)	(0.120)
Y_{t-1}	-0.046***	-0.038***	-0.062***	-0.223***	-0.242***	-0.020***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)	(0.007)
$\Delta_1 Y_{t-1}$	0.083***	0.028**	0.066***	-0.092***	-0.038***	0.015
	(0.010)	(0.013)	(0.011)	(0.011)	(0.010)	(0.027)
Age	-0.150***	-0.101***	-0.096***	-0.002	-0.064***	1.016***
	(0.004)	(0.005)	(0.005)	(0.018)	(0.013)	(0.079)
Constant	1.036***	0.864***	1.137***	-0.322***	3.002***	-24.792***
	(0.037)	(0.053)	(0.042)	(0.109)	(0.104)	(0.728)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**40,747**	**40,747**	**40,747**	**40,747**	**40,747**	**40,226**

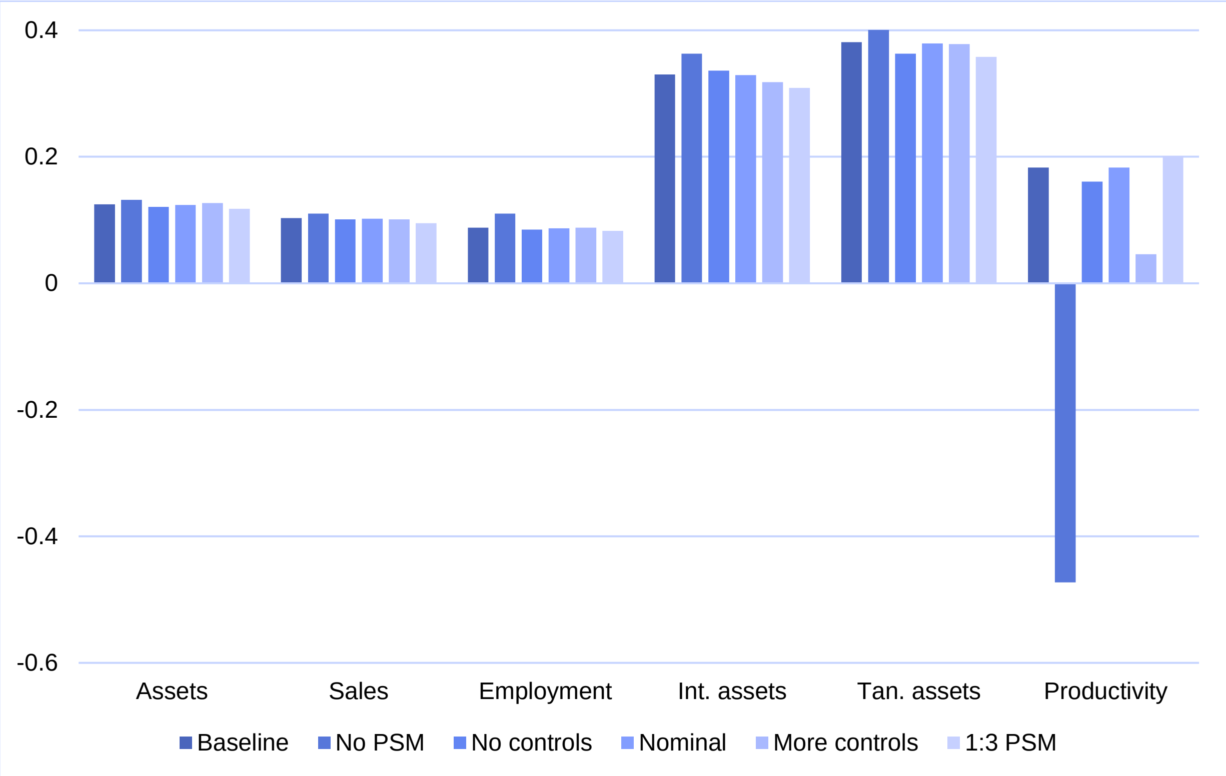
Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on Δ3Y, the 3-year growth in Y (the logarithm of total assets, sales, employment cost, intangible fixed assets, tangible fixed assets, and labour productivity measured as the ratio of sales to employment cost) from the end of year T-1 to the end of year T+2, where T is the signature year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level of the variable of interest. Δ1Yt-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

The results in Table 7 are fairly robust to alternative choices for the control group and control variables. For the sake of brevity, we report all the tables of the robustness tests in the Annexes and only show, in Figure 3, the treatment effects estimated using different methods. We replicate the baseline analysis by:

- Changing the matching parameters (with 1:3 PSM rather than 1:1, see Table A1.1, and without any PSM, see Table A1.2);
- Recalculating of the dependent variable (using nominal instead of inflation adjusted amounts);
- Modifying the specification (excluding controls and using a more complete set of controls, see Table A1.3 and Table A1.4);
- Varying the time horizon (we look at 2 and 4-year growth, see Table A1.5 and Table A1.6);
- Including an Inverse Mills Ratio (IMR, Heckman 1979) to control for selection in the sample (see Table A1.7).

Overall results are very robust for all the treatment effects that are statistically significant in Table 7 (total assets, sales, employment cost, intangible fixed assets, and tangible fixed assets). Results are less stable for labour productivity, consistent with the fact that the standard error of the estimate is very large in Table 7.

Figure 3 – Treatment effect estimates with different specifications



4.1.2 Growth moderators

In this section we study how the average treatment effect estimated in the previous section varies across a series of dimensions (moderators):

- Size (total assets<100k EUR, between 100k and 300k and more than 300k);
- Age (less than 5 years old, between 5 and 9, 10 or more);[10]
- Intangible ratio (intangible/total assets =0%, between 0% and 1%, between 1% and 5%, more than 5%);
- Industry (by macro-industries);
- Country;
- Signature year.

Results are reported in Table A1.8 in Annexes, in which the excluded baseline categories are: Total assets ≤ 100k, Age < 5y, Industry AB, Int. ratio = 0%, Signature year 2015. To make the results Table A1.8 more readable, we calculate the treatment effect for each category as linear

[10] It is worth reminding that companies younger than 2 years in the signature year are systematically excluded from the analysis because of the control for growth between T-2 and T-1.

combination of the parameters keeping all moderators at means except for the focal one. E.g., when comparing treatment effects over different asset classes, we consider a firm which is “average” in all other characteristics, except for its size. This allows us to understand the importance of each dimension keeping all other dimensions constant. We illustrate results in Figure 4, where the dependent variables are logarithmic differences between two years after the signature year and one year before.

Figure 4 shows that companies of different sizes benefit from guaranteed loans in a different way. The treatment effect on total assets growth decreases with size. In contrast, the treatment effect on sales growth increases with size (the treatment effect on employment does not vary significantly with size). Therefore, larger SMEs see gains in labour productivity (measured as sales to employment cost) from guaranteed loans whereas smaller SMEs do not. We also observe a difference in the composition of fixed assets growth: intangible fixed assets grow faster in larger SMEs and tangible fixed assets grow faster in smaller SMEs.

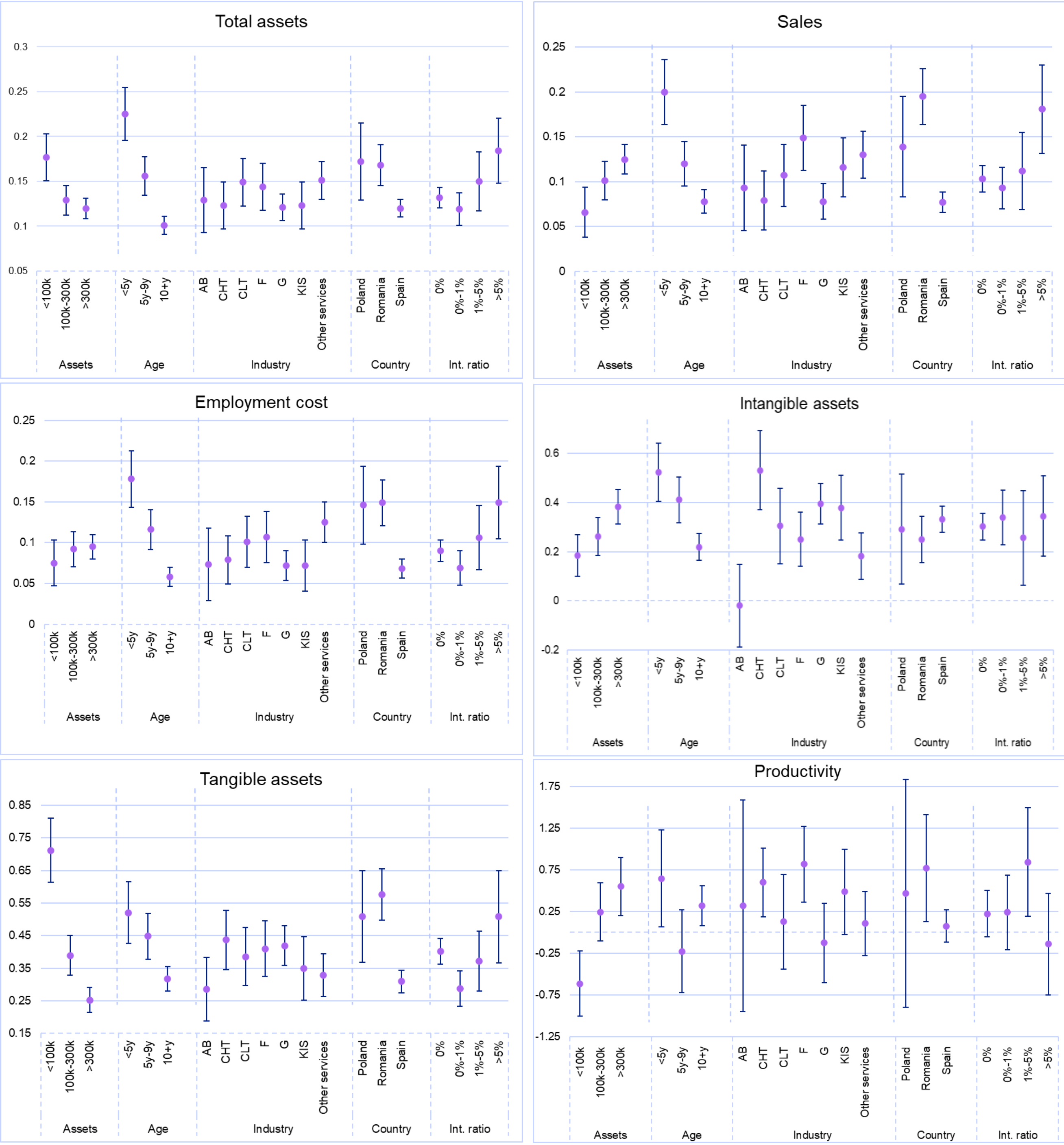
The results are more straightforward when it comes to age: guaranteed loans are associated with larger treatment effects on growth in younger companies along all dimensions (total assets, sales, employment cost, intangible fixed assets, tangible fixed assets, and, to a smaller extent, labour productivity).

We do not observe statistically significant differences in treatment effects on total assets, sales and employment across industries. However, we do observe some differences in the treatment effects of tangible and intangible asset growth that reflect the specific nature of the different industries. For instance, intangible asset growth is significantly smaller in AB (Agriculture, forestry and fishing; Mining and quarrying) than other industries.

Along most dimensions, treatment effects seem to be smaller in the Spanish sample than in SMEs in the other two countries. This might suggest that treatment effects are larger in countries with less developed financial systems, also in line with previous findings (e.g., Asdrubali and Signore, 2015; Brault and Signore, 2019).

Finally, along most dimensions, the treatment effect of guaranteed loans is larger in companies that have more intangible fixed assets, which are the most likely to be innovative and more exposed to financial constraints (e.g., Almeida and Campello, 2007).

Figure 4 – Treatment effect estimation by size, age, industry, country and intangible ratio



Legend: The figure illustrates 3-year treatment effect estimates for the growth of total assets, sales, employment cost, intangible fixed assets, tangible fixed assets, and labour productivity (sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The treatment effect is interacted with categorical variables capturing size (total assets in 2015 values), age (in years at time of signature), industry (in macro-industries), country, and intangible ratio (intangible to total assets). For each category, the treatment effect is calculated keeping all other dimensions at their mean. 95% confidence intervals are shown.

4.1.3 Fixed-effects regression

In Table 8 we report the results of fixed-effects regression models for the panel dataset.

Table 8 – Fixed-effect panel data model

	ΔAssets$_t$	ΔSales$_t$	ΔEmployment$_t$	ΔInt. assets$_t$	ΔTan. assets$_t$	ΔProductivity$_t$
Gloan$_t$	0.036***	0.016***	0.021***	0.101***	0.134***	-0.001
	(0.002)	(0.003)	(0.003)	(0.013)	(0.008)	(0.001)
Y_{t-1}	-0.273***	-0.259***	-0.318***	-0.424***	-0.397***	-0.000*
	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.000)
ΔY_{t-1}	0.007**	-0.019***	0.064***	0.105***	0.055***	-0.382***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
Age	0.055***	-0.019***	0.100***	0.014	0.206***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.022)	(0.016)	(0.002)
Constant	3.407***	3.450***	3.443***	1.142***	3.891***	0.064***
	(0.044)	(0.059)	(0.030)	(0.048)	(0.046)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**321,274**	**318,778**	**311,846**	**315,513**	**317,112**	**308,248**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff panel estimates on year-on-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. Gloan is an indicator variable equal to one for beneficiaries from the signature year. Yt-1 is the lagged log of the variable of interest. ΔYt-1 is the lagged year-on-year growth in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by firm and year. Robust standard errors in round brackets.

The dependent variables of these models are logarithmic annual growth of assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity. The key variable of interest is a step variable that equals 1 starting from the signature year. The controls include the beginning-of-year level of the dependent variable, the growth rate over the previous year, and age (firm and year fixed effects are also included). Overall, the results confirm those from the previous section: beneficiaries have a faster growth rate than matched companies in assets, sales, employment, intangible and tangible fixed assets. The order of magnitude of the treatment effect is comparable to what found in the previous section (which refers to total growth over the three years starting at the beginning of the signature year). As in the cross-sectional analysis, the average treatment effect of labour productivity growth is not significantly different from zero. Our robustness checks include the use of the alternative 1:3 matching strategy (see Table A2.1 in Annexes) and the inclusion of different sets of controls (Table 8).

We can augment the fixed-effect specification to include time-varying treatment effect estimation. We "decompose" the step dummy into 5 different dummies that identify the treatment effect in the signature year T ($Gloan_T$), in each of the three following years ($Gloan_{T+1}$,$Gloan_{T+2}$,$Gloan_{T+3}$), and over the following years ($Gloan_{T+4 \text{ or more}}$). Results are in Table 9.

Table 9 – Staggered fixed-effect panel data model

	$\Delta Assets_t$	$\Delta Sales_t$	$\Delta Employment_t$	$\Delta Int.\ assets_t$	$\Delta Tan.\ assets_t$	$\Delta Productivity_t$
$Gloan_T$	0.085***	0.027***	0.036***	0.087***	0.220***	-0.007***
	(0.003)	(0.003)	(0.003)	(0.014)	(0.009)	(0.001)
$Gloan_{T+1}$	0.015***	0.027***	0.030***	0.079***	0.089***	0.004***
	(0.002)	(0.003)	(0.003)	(0.014)	(0.008)	(0.001)
$Gloan_{T+2}$	0.005**	0.008**	0.008***	0.082***	0.072***	0.002
	(0.003)	(0.003)	(0.003)	(0.014)	(0.008)	(0.001)
$Gloan_{T+3}$	0.003	0.000	0.003	0.071***	0.050***	0.001
	(0.003)	(0.004)	(0.004)	(0.016)	(0.009)	(0.002)
$Gloan_{T+4 \text{ or more}}$	0.006	0.010	0.001	0.060**	0.031**	0.006**
	(0.005)	(0.007)	(0.006)	(0.026)	(0.015)	(0.003)
Y_t	-0.272***	-0.259***	-0.318***	-0.424***	-0.396***	-0.000*
	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.000)
ΔY_{t-1}	0.006**	-0.019***	0.064***	0.105***	0.054***	-0.382***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
Age	0.056***	-0.019***	0.100***	0.014	0.207***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.022)	(0.016)	(0.002)
Constant	3.389***	3.449***	3.442***	1.134***	3.870***	0.065***
	(0.044)	(0.059)	(0.030)	(0.048)	(0.046)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**321,274**	**318,778**	**311,846**	**315,513**	**317,112**	**308,248**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff panel estimates on year-on-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. GloanT is an indicator variable equal to one for beneficiaries in the signature year. GloanT+1- GloanT+3 are indicator variables equal to one for beneficiaries 1-3 years after the signature year. Gloant+4 and more is an indicator variable equal to one for beneficiaries 4 or more years after the signature year. Yt is the lagged log of the variable of interest. ΔYt-1 is the lagged year-on-year growth in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by firm and year. Robust standard errors in round brackets.

The treatment effect on asset growth is concentrated in the signature year, but we see a significantly higher growth rate in total assets also in the two years following the signature year, and no evidence of mean reversion (i.e., no evidence of lower-than-average growth in following years). The treatment effect is more stable across years for sales and employment cost, with the effect in the signature year having approximately the same magnitude as in the following year. Again, no evidence of mean reversion in later year emerges from the results. Growth rates of intangible and tangible fixed assets are even more protracted. The effect is larger in the signature year than in the following years, but the growth rate is positive and significant in each of the following four periods. Finally, because of the time lag between the growth in production inputs and production output, we observe a significant decline in labour productivity in the signature year, with an offsetting amount in the following year. In other words, the non-significant treatment effect we observe over a three-year period results from an initial decline in labour productivity (corresponding to the increase in the production inputs) followed by an increase in labour productivity (when the output of production is realized). This result confirms that studies on the effect of guaranteed loans (and policies that affect production growth in general) on productivity should be carried out with a sufficiently long horizon to ensure a comprehensive view of the treatment effect.

4.1.4 Alternative matching

In this section we repeat the main analysis using an alternative matching method in which the number of employees is used instead of employment cost in the initial PSM step, as dependent growth variable, and as denominator for the calculation of labour productivity (here defined as sales to number of employees). Although conceptually similar, we prefer to use employment cost in our main analysis because it tends to be a more reliable and precise measure of employment. However, for one of the countries included in this study (Greece), employment cost is not available in Orbis and hence the number of employees becomes the best available employment proxy. Unfortunately, as illustrated previously (see column VI of Table 2), although this measure is largely available for beneficiaries in Greece, it is not available for a representative sample of Polish beneficiaries, which leads us to exclude this country for this analysis altogether. We show the results of the baseline estimates in Table 10.

There are several reasons why results in Table 10 might substantially differ from those in Table 7. In order of increasing importance: matching is done on a slightly different set of variables (number of employees instead of employment cost); a different set of countries is included in the study (Romania, Spain and Greece instead of Poland); and some dependent variables are calculated differently, specifically employment (again, in terms of number, not cost) and labour productivity (sales to number of employees, instead of sales to employment cost).

However, reassuringly, results are very similar for growth in assets, sales, intangible fixed assets and tangible fixed assets. The effect of guarantees on the growth of the number of employees is 0.061, which is slightly less than the 0.088 found in the main regression for employment cost, but still positive and significant. The effect on labour productivity is still not positive nor significant, like in Table 7 (the two coefficients are not comparable because the two ratios have different units of measurement).

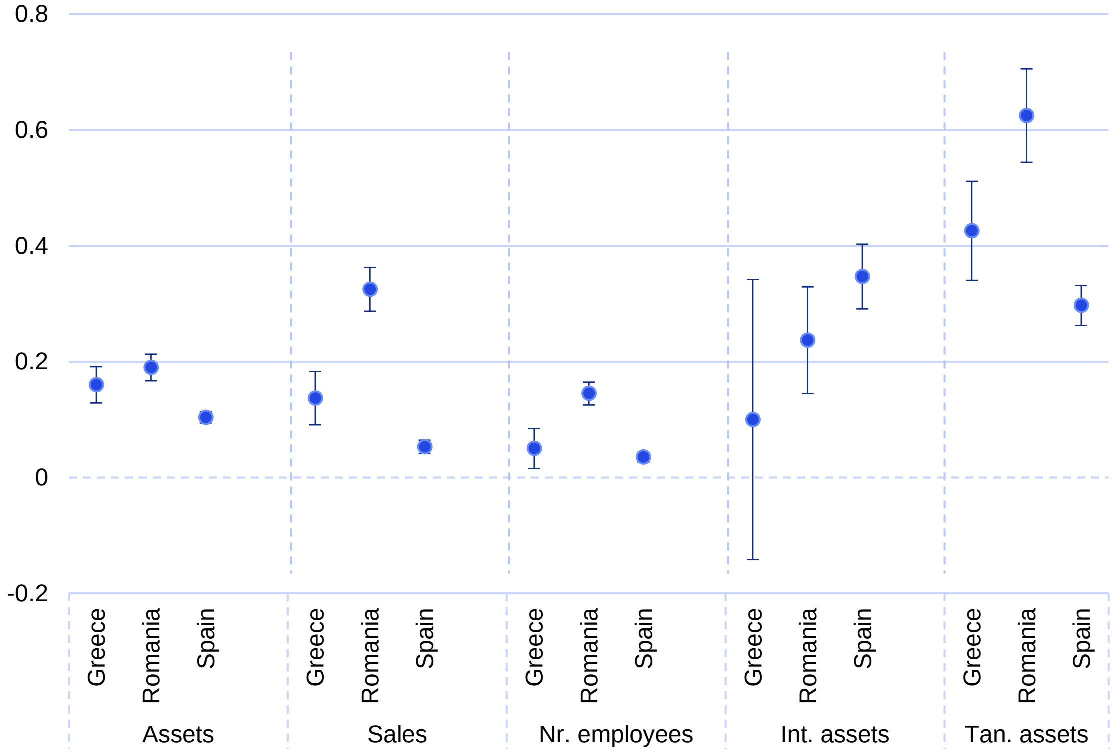
Table 10 – Cross-sectional effects for alternative sampling

	Δ_3Assets	Δ_3Sales	Δ_3Empl. No.	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity (Empl. No.)
Gloan	0.120***	0.121***	0.061***	0.329***	0.381***	28.577
	(0.005)	(0.007)	(0.005)	(0.028)	(0.018)	(1101.355)
Y_t	-0.046***	-0.019***	-0.038***	-0.222***	-0.239***	-0.040***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.007)
$\Delta_1 Y_{t-1}$	0.092***	0.056***	-0.016	-0.097***	-0.032***	-0.238***
	(0.011)	(0.016)	(0.011)	(0.011)	(0.010)	(0.021)
Age	-0.145***	-0.092***	-0.076***	0.025	-0.079***	-949.770
	(0.005)	(0.006)	(0.004)	(0.019)	(0.014)	(793.502)
Constant	1.262***	0.811***	0.452***	0.546***	3.658***	19099.846***
	(0.040)	(0.058)	(0.020)	(0.122)	(0.105)	(5369.228)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**37,668**	**37,668**	**37,668**	**37,668**	**37,668**	**37,749**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 3-year growth in total assets, sales, number of employees, intangible fixed assets, tangible fixed assets and labour productivity (Sales to number of employees). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt is the pre-treatment level (in logs) of the variable of interest. Δ1Yt-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

We re-estimate the moderation effects using the same methodology as in section 4.1.2 under the alternative sampling. In the next figure, we report the differences in terms of country (the other moderating effects being very close to what is shown in the main analysis).

Figure 5 – Moderating effects of country on treatment effects in the alternative matching



Results for Greece are generally intermediate between those of Romania and those of Spain but still positive and significant, except growth in intangible fixed assets, that is positive but not statistically significant (the standard error is very large).[11]

4.2 Survival

We follow a similar approach to analyse the impact of guaranteed loans on the survival of beneficiaries with respect to a control group of similar companies. An important difference is that the unit of analysis in this case is the company and not the loan-year observation. We are interested in understanding if beneficiaries' chances to fail are higher or lower after treatment.

4.2.1 Sampling for survival

To sample beneficiaries, we focus on the companies with complete accounting information in the year before the signature year, similarly to those described in Column IV of Table 2. For companies that receive multiple guaranteed loans, we consider the first signature year. We do not require the availability of accounting information after treatment, because this would imply to systematically exclude failed companies (which do not register their accounting data anymore), which are instead the focus of our analysis. For the same reason, when we repeated the PSM algorithm described in section 3.4.2 to select an appropriate control group, we did not exclude companies without accounting data in T+2.

[11] The huge variations of results for intangible assets could be explained by differences in accounting standards across countries.

We checked the balancing of the matching with t-tests of our regressors, finding generally good properties. The unconditional probability of failure is lower for treated companies (5.46%) than for matched untreated companies (8.50%).

4.2.2 Main effects

Table 11 reports the results of probit models in which the dependent variable is equal to 1 for companies that went bankrupt between the signature year and the end of 2023. The baseline model is presented in Column I and shows a negative coefficient for *GLoan*, indicating lower failure rates for treated companies. Marginal effects suggest that treated companies have a failure rate that is 2.8 p.p. lower than matched companies.

Results are robust when we consider all potential control group companies (or in other terms we do not use PSM to select the control group, column II), when we do not add control variables (column III), when we add more control variables (column IV), when we do not correct for inflation (column V) or when we do a 1:3 instead of a 1:1 PSM (column VI).

As a last robustness check, we also used a Cox (1972) survival model, whose dependent variable is the hazard rate of failure in a given year conditional of having survived until that year. The Cox model accommodates data censoring in 2023, the end of the observation period. In Column VII, we find that receipt of the loan considerably reduces the risk of being dissolved.

The fact that the receipt of guaranteed loans has a positive effect on survival excludes the possibility that the results illustrated earlier on company growth are affected by an upward survivorship bias. If anything, we may have underestimated the treatment effect along the other performance dimensions.

Table 11– Survival analysis

	I Baseline (1:1 matching)	II No matching	III No controls	IV All controls	V No correction for inflation	VI 1:3 matching	VII Cox
Gloan	-0.227***	-0.291***	-0.228***	-0.229***	-0.234***	-0.227***	-0.504***
	(0.017)	(0.012)	(0.016)	(0.017)	-0.017	(0.014)	(0.035)
ΔLn(Total assets $_{T-1}$)	-0.028	-0.233***	n.a	-0.024	-0.048**	-0.036*	-0.122**
	(0.023)	(0.005)	n.a	(0.026)	-0.023	(0.019)	(0.051)
Ln(Total assets $_{T-1}$)	0.033***	-0.051***	n.a	0.036***	0.028***	0.033***	0.081***
	(0.007)	(0.001)	n.a	(0.013)	-0.007	-0.005	(0.014)
Leverage $_{T-1}$	0.089***	0.019***	n.a	0.075***	0.087***	0.095***	0.114***
	(0.010)	(0.001)	n.a	(0.010)	-0.01	(0.008)	(0.011)
Cash ratio $_{T-1}$	-0.376***	-0.022***	n.a	-0.433***	-0.359***	-0.387***	n.a
	(0.066)	(0.008)	n.a	(0.067)	-0.064	(0.053)	n.a
Age	-0.087***	-0.018***	n.a	-0.083***	-0.083***	-0.097***	-0.193***
	(0.013)	(0.002)	n.a	(0.013)	-0.012	(0.010)	(0.026)
Constant	-1.455***	-1.999***	-1.374***	-1.159***	-1.340***	-1.409***	n.a
	(0.117)	(0.053)	(0.011)	(0.127)	(0.114)	(0.091)	n.a
Industry FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Other controls	No	No	No	Yes	No	No	No
N	**55,142**	**1,147,972**	**57,491**	**55,142**	**57,471**	**102,714**	**54,772**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports probit (Columns I-VI) and Cox (Column VII) estimates of the failure of treated and matched companies. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. Robust standard errors in round brackets.

4.2.3 Survival moderators

As a last analysis, we assess the impact of moderators on the effect of guaranteed loans on failure rates. To do so, we include the usual set of moderators, i.e., age classes, size classes, industry, country, intangible ratios classes, and signature years, in our baseline probit specification. We then computed marginal effects to allow for better interpretation of the results.

Table 12 reports average marginal effects of *GLoan* on the probability of failing for the different levels of the moderators. We find larger reductions in the failure rates for treated companies in the smallest asset class (<100k), the oldest companies (>5 years), in Poland, without intangibles and in less recent signature years.

Table 12 – Moderators of treatment effect on failure-rate

	Average Marginal Effect	Std.Dev.
Total assets class		
<100k	-0.063	0.006***
100k-300k	-0.030	0.004***
≥300k	-0.015	0.003***
Age Class		
<5 years	-0.015	0.006**
5-9 years	-0.027	0.005***
≥10 years	-0.030	0.003***
Country		
Poland	-0.076	0.009***
Romania	0.003	0.004
Spain	-0.031	0.003***
Intangible ratio class		
Int ratio = 0%	-0.030	0.003***
0%<Int ratio<1%	-0.024	0.005***
1%<Int ratio<5%	-0.020	0.011*
Int ratio >5%	-0.026	0.010***
Signature year		
2015	-0.064	0.011***
2016	-0.031	0.008***
2017	-0.024	0.006***
2018	-0.028	0.005***
2019	-0.033	0.005***
2020	-0.016	0.003***

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10%

5 Conclusions

In this report, we have presented the results of the analysis of the treatment effect of the COSME Loan Guarantee Facility (LGF) in four European countries (Greece, Poland, Romania, and Spain) during 2015-2023.

We build on the existing literature that has studied the treatment effect of guaranteed loans on the growth and survival of beneficiaries and use well-established diff-in-diff models based on Propensity Score Matching to select an appropriate counterfactual.

The results show that over three years, guaranteed loan beneficiaries grow substantially more than matched companies in terms of assets (13.3 p.p.), sales (10.8 p.p.), employment (9.2 p.p.), intangible fixed assets (39.1 p.p.), and tangible fixed assets (46.4 p.p.). All these estimates are statistically significant at the 1% level and stable across different choices of matching and specification. There is no evidence of a significant change in labour productivity over the 3-year time horizon. We find that the treatment effect is generally larger for companies that are exposed to more significant financial constraints (younger, and with lower asset tangibility). The effect on total assets is greater for smaller firms (i.e., total assets<100k EUR), while the effect on sales is greater for larger firms (i.e., total assets >300k EUR). Larger firms also experience a positive effect on labour productivity growth. In terms of survival, beneficiaries are 2.8 percent more likely than matched companies to survive until the end of 2023. We find a more positive effect on survival for smaller and older companies.

These results confirm what was shown in studies conducted on earlier programs like CIP and MAP (e.g., Asdrubali and Signore, 2015; Bertoni et al. 2019; Brault and Signore, 2019): guaranteed-loan beneficiaries outperform matched companies both in terms of growth and survival, without a significant reduction in productivity and over an extended period (in this study we can look at a performance up to 4 years after the treatment before the sample becomes too small).

The results are reassuring because, in line with the COSME objective of improving access to finance of SMEs that would otherwise be credit constrained, we find that guaranteed loans are associated with a substantial additional growth of the beneficiaries. This holds in each of the four countries in our analysis, and for each of the growth variables (assets, sales, employment) we consider. Beneficiaries also invest substantially more in tangible and, more interestingly, intangible fixed assets. Without COSME support, a significant share of SMEs would have been unlikely to undertake these investments. This is particularly clear in some sub-groups of SMEs, which are more severely affected by credit rationing (e.g. young, high intangible companies).

Most other studies on the effects of guaranteed loans have not found a significant increase in the beneficiaries' investments in intangible fixed assets. Our results in this sense are possibly due to the specific nature of the guaranteed loans in our sample, some of which are reserved for transactions without collateral. Because of their nature, intangible fixed assets are less likely than tangible fixed assets and current assets to be used as collateral, and hence could be particularly favoured by these types of guaranteed loans. It would be interesting, in future research, to better understand the link between the contractual characteristics of the agreements between the EIF and the intermediaries, as well as the observed effect of guaranteed loans on growth and investments.

We do observe some significant differences in the size of the treatment effect across countries. The degree of financial development in the country also drives to some extent the result: in countries with lower access to finance constraints (in our case Spain), treatment effects tend to be lower (though still positive).

Compared to previous programs, COSME seems to have significantly benefitted companies in Knowledge-intensive services (KIS) and with high intangibles, potentially reflecting an improved targeting of the financial offering towards these SMEs.

Box 1: COSME's implementation design and enhanced impact on riskier SMEs

Compared to previous programs, COSME introduced a new implementation strategy that might at least partially explain the higher impact. In fact, COSME's predecessor programs were typically aiming at increasing the volumes disbursed by targeting SMEs with risk profiles in line with the intermediary portfolio.

COSME is designed to shift the intermediary's portfolio risk. A two-tier approach was developed to achieve this: one option ensures the financial intermediary targets SMEs with a risk profile 30% higher than the average company in their portfolio. The second option allows the financial intermediary to increase disbursed volumes, but only for the riskiest 25% of their portfolio. This design ensures financial accessibility to riskier SMEs, thus increasing the program's impact

In fact, the program aims to strike a balance between maximizing the impact (by targeting riskier profiles) while maintaining a financial sustainability and ease of implementation.

A particularly important aspect from a policy perspective is that guaranteed loans do not cause unwanted effects. First, if beneficiaries were not financially constrained to begin with, credit expansion could generate a permanent decline in productivity, because low-quality investments would be financed with the proceeds of the loan. However, here, we see that – besides a temporary dip due to the different timing between the costs and benefits of investments – this is not the case: long-term labour productivity does not decline for beneficiaries.

Second, one could worry that an increase in leverage following the guaranteed loan could result in an increase in failure rates. Again, this is not the case here: guaranteed loans are not associated with an increase in bankruptcy, and beneficiaries are less likely to fail than non-beneficiaries. This is consistent with the fact that beneficiaries are financially constrained to begin with, and that they use the proceeds of the guaranteed loans for productive investments. This indicates that credit rationing is a particular existential issue for this target group.

Annexes

Annex 1: Cross sectional analysis

Table A1.1: Cross-sectional diff-in-diff regression with 1:3 PSM

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.118***	0.095***	0.083***	0.309***	0.358***	0.201**
	(0.004)	(0.006)	(0.005)	(0.023)	(0.014)	(0.101)
Y_{t-1}	-0.048***	-0.037***	-0.064***	-0.220***	-0.242***	-0.021**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.009)
$\Delta_1 Y_{t-1}$	0.073***	0.032***	0.066***	-0.099***	-0.041***	0.004
	(0.008)	(0.010)	(0.009)	(0.009)	(0.008)	(0.024)
Age	-0.153***	-0.101***	-0.100***	-0.009	-0.083***	1.079***
	(0.004)	(0.004)	(0.004)	(0.015)	(0.010)	(0.068)
Constant	1.084***	0.869***	1.177***	-0.371***	3.053***	-24.854***
	(0.030)	(0.042)	(0.034)	(0.090)	(0.084)	(0.636)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**75,712**	**75,712**	**75,712**	**75,712**	**75,712**	**74,629**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on Δ3Y, the 3-year growth in Y (the logarithm of total assets, sales, employment cost, intangible fixed assets, tangible fixed assets, and labour productivity measured as the ratio of sales to employment cost) from the end of year T-1 to the end of year T+2, where T is the signature year. Each guaranteed loan beneficiary is matched to 3 non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level of the variable of interest. Δ1Yt-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm’s age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

Table A1.2: Cross-sectional diff-in-diff regression without PSM

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.132***	0.110***	0.110***	0.363***	0.413***	-0.473***
	(0.004)	(0.004)	(0.004)	(0.019)	(0.012)	(0.081)
Y_{t-1}	-0.044***	-0.049***	-0.053***	-0.225***	-0.209***	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
$\Delta_1 Y_{t-1}$	0.069***	-0.019***	0.032***	-0.110***	-0.046***	-0.068***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.011)
Age	-0.128***	-0.086***	-0.079***	0.037***	-0.050***	1.001***
	(0.001)	(0.002)	(0.001)	(0.005)	(0.004)	(0.025)
Constant	1.316***	1.315***	1.256***	2.223***	4.043***	-15.684***
	(0.075)	(0.087)	(0.056)	(0.454)	(0.123)	(0.718)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**441,819**	**438,847**	**433,151**	**435,198**	**436,088**	**423,251**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 3-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are compared to all potential control group (PCG) companies obtained from the extraction grid. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level (in logs) of the variable of interest. Δ1Y t-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

Table A1.3: Cross-sectional diff-in-diff regression without controls

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.121***	0.101***	0.085***	0.336***	0.363***	0.161
	(0.006)	(0.007)	(0.007)	(0.029)	(0.019)	(0.138)
Constant	0.144***	-0.011**	0.084***	-0.156***	-0.006	-9.266***
	(0.004)	(0.005)	(0.005)	(0.020)	(0.014)	(0.102)
Industry FE	No	No	No	No	No	No
Country FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
N	**40,747**	**40,747**	**40,747**	**40,747**	**40,747**	**40,226**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 3-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Robust standard errors in round brackets.

Table A1.4: Cross-sectional diff-in-diff regression with all controls

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.127***	0.101***	0.088***	0.318***	0.378***	0.046
	(0.005)	(0.007)	(0.006)	(0.027)	(0.017)	(0.029)
ΔLn(Total assets$_{T-1}$)	0.027**	0.143***	0.140***	0.173***	0.251***	0.002
	(0.012)	(0.014)	(0.013)	(0.042)	(0.035)	(0.067)
ΔLn(Sales$_{T-1}$)	0.047***	-0.083***	0.086***	0.012	0.043	0.178
	(0.013)	(0.020)	(0.016)	(0.046)	(0.039)	(0.126)
ΔLn(Emp. cost$_{T-1}$)	0.062***	0.113***	-0.022	0.249***	0.129***	-0.297**
	(0.015)	(0.020)	(0.018)	(0.051)	(0.044)	(0.136)
ΔLn(Int. assets$_{T-1}$)	0.003**	0.005**	0.002	-0.079***	0.010**	-0.018**
	(0.002)	(0.002)	(0.002)	(0.011)	(0.005)	(0.008)
ΔLn(Tang. assets$_{T-1}$)	0.014***	0.008**	0.009***	0.008	-0.050***	-0.008
	(0.003)	(0.004)	(0.003)	(0.011)	(0.011)	(0.015)
ΔProductivity$_{T-1}$	0.001*	0.004***	-0.000	0.001	0.003	0.004
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.010)
Ln(Total assets$_{T-1}$)	-0.146***	0.055***	0.025***	0.236***	0.259***	-0.151***
	(0.005)	(0.007)	(0.006)	(0.020)	(0.019)	(0.035)
Ln(Sales$_{T-1}$)	0.111***	-0.152***	0.113***	0.052*	0.085***	-1.906***
	(0.008)	(0.012)	(0.010)	(0.030)	(0.025)	(0.087)
Ln(Emp. cost$_{T-1}$)	0.013*	0.074***	-0.181***	0.117***	0.004	1.980***
	(0.007)	(0.009)	(0.008)	(0.029)	(0.022)	(0.078)
Ln(Int. assets$_{T-1}$)	0.002***	0.004***	0.005***	-0.278***	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.004)
Ln(Tang. assets$_{T-1}$)	-0.002	0.004**	0.006***	-0.001	-0.339***	0.045***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.010)	(0.009)
Productivity$_{T-1}$	0.001*	0.001**	0.002***	-0.003*	-0.002*	-0.738***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.008)
Leverage$_{T-1}$	-0.010	0.019**	-0.006	0.054***	-0.037	-0.133***
	(0.009)	(0.008)	(0.008)	(0.017)	(0.023)	(0.030)
Cash ratio$_{T-1}$	0.082***	0.045*	0.141***	-0.127	0.328***	0.139
	(0.024)	(0.026)	(0.025)	(0.086)	(0.081)	(0.093)
Age	-0.115***	-0.099***	-0.079***	-0.116***	-0.102***	0.078***
	(0.004)	(0.006)	(0.005)	(0.021)	(0.014)	(0.024)
Constant	0.684***	0.750***	0.367***	-5.223***	-0.429***	0.821***
	(0.043)	(0.054)	(0.048)	(0.202)	(0.129)	(0.248)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**40,747**	**40,747**	**40,747**	**40,747**	**40,747**	**40,226**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 3-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Robust standard errors in round brackets.

Table A1.5: Treatment effect estimation on 2-year growth

	Δ_2Assets	Δ_2Sales	Δ_2Employment	Δ_2Int. assets	Δ_2Tan. assets	Δ_2Productivity
Gloan	0.119***	0.092***	0.078***	0.257***	0.344***	0.197*
	(0.004)	(0.005)	(0.005)	(0.023)	(0.014)	(0.119)
Y_{t-1}	-0.041***	-0.032***	-0.057***	-0.161***	-0.204***	-0.019***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
$\Delta_1 Y_{t-1}$	0.057***	0.020*	0.060***	-0.024***	-0.032***	0.016
	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)	(0.027)
Age	-0.119***	-0.085***	-0.083***	-0.021	-0.065***	1.008***
	(0.004)	(0.004)	(0.004)	(0.016)	(0.011)	(0.078)
Constant	0.855***	0.745***	1.023***	0.001	2.511***	-24.644***
	(0.031)	(0.042)	(0.035)	(0.095)	(0.092)	(0.726)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**40,430**	**40,392**	**40,315**	**40,207**	**40,335**	**39,886**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 2-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between one year after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level (in logs) of the variable of interest. Δ1Y t-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

Table A1.6: Treatment effect estimation on 4-year growth

	Δ_4Assets	Δ_4Sales	Δ_4Employment	Δ_4Int. assets	Δ_4Tan. assets	Δ_4Productivity
Gloan	0.112***	0.098***	0.072***	0.328***	0.342***	0.101
	(0.007)	(0.010)	(0.008)	(0.035)	(0.023)	(0.139)
Y_{t-1}	-0.048***	-0.028***	-0.065***	-0.267***	-0.265***	-0.024**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.009)	(0.010)
$\Delta_1 Y_{t-1}$	0.087***	0.023	0.061***	-0.124***	-0.078***	-0.018
	(0.014)	(0.017)	(0.015)	(0.014)	(0.014)	(0.033)
Age	-0.173***	-0.117***	-0.119***	0.015	-0.062***	1.081***
	(0.006)	(0.008)	(0.007)	(0.025)	(0.018)	(0.096)
Constant	1.138***	0.792***	1.334***	-0.251	3.509***	-26.320***
	(0.052)	(0.075)	(0.059)	(0.167)	(0.136)	(0.989)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**28,056**	**27,895**	**27,639**	**27,823**	**27,907**	**27,493**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 4-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between three years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level (in logs) of the variable of interest. Δ1Yt-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

Table A1.7: Cross-sectional diff-in-diff regression controlling for sample selection

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.125***	0.103***	0.088***	0.330***	0.380***	0.188
	(0.005)	(0.007)	(0.006)	(0.027)	(0.017)	(0.120)
Y_{t-1}	-0.046***	-0.038***	-0.062***	-0.223***	-0.241***	-0.020***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)	(0.007)
$\Delta_1 Y_{t-1}$	0.083***	0.028**	0.066***	-0.093***	-0.039***	0.015
	(0.010)	(0.013)	(0.011)	(0.011)	(0.010)	(0.027)
Age	-0.162**	-0.035	-0.308***	0.621**	-0.402*	7.580***
	(0.077)	(0.094)	(0.083)	(0.282)	(0.239)	(1.928)
IMR	-0.066	0.385	-1.233**	3.645**	-1.971	38.327***
	(0.447)	(0.541)	(0.479)	(1.656)	(1.382)	(11.144)
Constant	1.224	-0.229	4.635***	-10.678**	8.598**	-133.707***
	(1.268)	(1.535)	(1.359)	(4.708)	(3.926)	(31.692)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**40,747**	**40,747**	**40,747**	**40,747**	**40,747**	**40,226**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on 3-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. Yt-1 is the pre-treatment level (in logs) of the variable of interest. Δ1Yt-1 is the pre-treatment growth (from two to one year before the signature year) in the variable of interest. Age is the logarithm of firm's age. IMR is the inverse Mills' ratio of the inclusion in the final sample (starting from the initial population of beneficiaries), calculated using total assets, age, and fixed effects for industry, year, and country. All models include fixed effects by industry (NACE 2-digit), country and year. Robust standard errors in round brackets.

Table A1.8 – Treatment effect moderators

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.300***	0.174***	0.202***	0.037	0.908***	0.070
	(0.041)	(0.053)	(0.048)	(0.187)	(0.127)	(1.211)
Gloan × (100k<Assets≤300k)	-0.048**	0.035*	0.017	0.078	-0.323***	0.860***
	(0.019)	(0.021)	(0.022)	(0.067)	(0.070)	(0.309)
Gloan × (Assets >300k)	-0.058***	0.059***	0.020	0.198***	-0.460***	1.165***
	(0.018)	(0.021)	(0.021)	(0.072)	(0.066)	(0.346)
Gloan × (5y<Age<10y)	-0.069***	-0.080***	-0.062**	-0.112	-0.073	-0.875**
	(0.022)	(0.026)	(0.026)	(0.089)	(0.073)	(0.446)
Gloan × (Age≥10y)	-0.124***	-0.122***	-0.121***	-0.304***	-0.203***	-0.326
	(0.019)	(0.023)	(0.023)	(0.080)	(0.064)	(0.388)
Gloan × (Industry CHT)	-0.006	-0.014	0.006	0.550***	0.151*	0.278
	(0.027)	(0.035)	(0.033)	(0.143)	(0.080)	(0.821)
Gloan × (Industry CLT)	0.020	0.014	0.028	0.324**	0.100	-0.194
	(0.027)	(0.036)	(0.033)	(0.138)	(0.079)	(0.848)
Gloan × (Industry F)	0.015	0.056	0.033	0.270**	0.124	0.496
	(0.028)	(0.037)	(0.034)	(0.123)	(0.079)	(0.832)
Gloan × (Industry G)	-0.008	-0.016	-0.002	0.415***	0.133*	-0.447
	(0.024)	(0.031)	(0.029)	(0.113)	(0.069)	(0.843)
Gloan × (Industry KIS)	-0.006	0.023	-0.002	0.398***	0.063	0.167
	(0.028)	(0.036)	(0.034)	(0.133)	(0.086)	(0.849)
Gloan × (Industry Other serv.)	0.022	0.037	0.051	0.201*	0.042	-0.214
	(0.026)	(0.034)	(0.032)	(0.117)	(0.072)	(0.818)
Gloan × (Romania)	-0.004	0.056	0.003	-0.042	0.067	0.303
	(0.030)	(0.039)	(0.034)	(0.149)	(0.098)	(0.932)
Gloan × (Spain)	-0.052**	-0.061*	-0.078***	0.041	-0.198**	-0.394
	(0.026)	(0.035)	(0.030)	(0.140)	(0.086)	(0.842)

	Δ3Assets	Δ3Sales	Δ3Employment	Δ3Int. assets	Δ3Tan. assets	Δ3Productivity
Table A1.8 continued						
Gloan × (0%<Int. ratio≤1%)	-0.012	-0.009	-0.021	0.036	-0.114***	0.016
	(0.013)	(0.017)	(0.016)	(0.078)	(0.041)	(0.339)
Gloan × (1%<Int. ratio≤5%)	0.018	0.009	0.016	-0.047	-0.029	0.620
	(0.021)	(0.027)	(0.026)	(0.123)	(0.061)	(0.431)
Gloan × (Int. ratio>5%)	0.052**	0.079**	0.059**	0.042	0.106	-0.364
	(0.024)	(0.032)	(0.029)	(0.107)	(0.090)	(0.402)
Gloan × (Year 2016)	0.059***	-0.025*	0.046***	0.300***	0.080*	-1.321***
	(0.012)	(0.014)	(0.015)	(0.056)	(0.044)	(0.220)
Gloan × (Year 2017)	0.038***	-0.038***	0.026*	0.291***	0.034	-0.778***
	(0.012)	(0.013)	(0.013)	(0.050)	(0.041)	(0.196)
Gloan × (Year 2018)	0.040***	-0.254***	-0.198***	0.205***	-0.022	0.081
	(0.012)	(0.013)	(0.013)	(0.050)	(0.041)	(0.194)
Gloan × (Year 2019)	0.072***	-0.117***	-0.145***	0.187***	0.059	-0.200
	(0.012)	(0.013)	(0.013)	(0.050)	(0.041)	(0.199)
Gloan × (Year 2020)	-0.016	-0.123***	-0.167***	0.397*	-0.406	0.918
	(0.037)	(0.043)	(0.046)	(0.206)	(0.327)	(1.247)
Constant	0.372***	0.279***	0.338***	-0.638***	0.116	-18.880***
	(0.032)	(0.041)	(0.037)	(0.140)	(0.100)	(0.908)
Assets FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Int. ratio FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**40,747**	**40,747**	**40,747**	**40,747**	**40,747**	**40,226**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on Δ3Y, the 3-year growth in Y (the logarithm of total assets, sales, employment cost, intangible fixed assets, tangible fixed assets, and labour productivity measured as the ratio of sales to employment cost) from the end of year T-1 to the end of year T+2, where T is the signature year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM. The dependent variables are logarithmic differences between two years after and one year before the signature year. Gloan is an indicator variable equal to one for beneficiaries. The variable is interacted with categorical variables capturing size (total assets in 2015 values), age (in years at time of signature), industry (in macro-industries), country, and intangible ratio (Intangible to total assets). The excluded categories are: Total assets≤100k, Age<5y, Industry AB, Int. ratio = 0%, Signature year 2015. Robust standard errors in round brackets.

Annex 2: Fixed-effect panel data models

Table A2.1: Fixed-effect panel data model, 1:3 PSM

	$\Delta Assets_t$	$\Delta Sales_t$	$\Delta Employment_t$	$\Delta Int.\ assets_t$	$\Delta Tan.\ assets_t$	$\Delta Productivity_t$
$Gloan_t$	0.036***	0.015***	0.020***	0.097***	0.134***	-0.003***
	(0.002)	(0.002)	(0.002)	(0.011)	(0.007)	(0.001)
Y_{t-1}	-0.273***	-0.258***	-0.318***	-0.425***	-0.396***	-0.000**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.000)
ΔY_{t-1}	0.008***	-0.019***	0.065***	0.104***	0.054***	-0.380***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Age	0.056***	-0.021***	0.101***	0.018	0.209***	-0.033***
	(0.005)	(0.006)	(0.005)	(0.019)	(0.013)	(0.002)
Constant	3.407***	3.435***	3.448***	1.138***	3.879***	0.066***
	(0.038)	(0.049)	(0.025)	(0.041)	(0.039)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**589,784**	**585,184**	**573,019**	**579,304**	**582,134**	**565,469**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff panel estimates on year-on-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM (1:3 ratio, nearest neighbor). Gloan is an indicator variable equal to one for beneficiaries from the signature year. Yt-1 is the lagged log of the variable of interest. ΔY t-1 is the lagged year-on-year growth in the variable of interest. Age is the logarithm of firm's age. All models include fixed effects by firm and year. Robust standard errors in round brackets.

Table A2.2: Fixed-effect panel data model, all controls

	ΔAssets$_t$	ΔSales$_t$	ΔEmployment$_t$	ΔInt. assets$_t$	ΔTan. assets$_t$	ΔProductivity$_t$
Gloan$_t$	0.036***	0.016***	0.021***	0.101***	0.134***	-0.001
	(0.002)	(0.003)	(0.003)	(0.013)	(0.008)	(0.001)
ΔLn(Total assets$_{T-1}$)	0.012***	0.094***	0.059***	0.004	0.026***	-0.000
	(0.003)	(0.004)	(0.003)	(0.013)	(0.010)	(0.001)
ΔLn(Sales$_{T-1}$)	-0.016***	-0.036***	-0.007**	0.020*	0.011	0.005***
	(0.003)	(0.005)	(0.003)	(0.012)	(0.008)	(0.002)
ΔLn(Emp. cost$_{T-1}$)	0.009***	0.042***	0.060***	0.003	0.012	-0.011***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.008)	(0.001)
ΔLn(Int. assets$_{T-1}$)	0.001	0.001*	0.002***	0.111***	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)
ΔLn(Tang. assets$_{T-1}$)	0.005***	0.002*	0.004***	0.013***	0.056***	0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.000)
ΔProductivity$_{T-1}$	0.032***	-0.003	0.030***	0.032	0.019	-0.105***
	(0.006)	(0.010)	(0.008)	(0.023)	(0.017)	(0.005)
Ln(Total assets$_{T-1}$)	-0.385***	0.073***	0.053***	0.171***	0.160***	-0.012***
	(0.003)	(0.005)	(0.004)	(0.014)	(0.011)	(0.002)
Ln(Sales$_{T-1}$)	0.076***	-0.412***	0.130***	0.043***	0.096***	0.007***
	(0.003)	(0.006)	(0.004)	(0.014)	(0.010)	(0.002)
Ln(Emp. cost$_{T-1}$)	0.024***	0.039***	-0.420***	0.074***	0.029***	-0.003**
	(0.003)	(0.004)	(0.004)	(0.012)	(0.008)	(0.002)
Ln(Int. assets$_{T-1}$)	0.002***	0.003***	0.002***	-0.438***	0.007***	0.000**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)
Ln(Tang. assets$_{T-1}$)	0.002**	0.006***	0.006***	0.007*	-0.422***	0.002***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.000)
Productivity$_{T-1}$	-0.025***	-0.101***	-0.000	-0.064**	-0.025	-0.507***
	(0.006)	(0.014)	(0.009)	(0.026)	(0.018)	(0.008)
Leverage$_{T-1}$	-0.065***	0.026***	-0.022***	0.047***	-0.088***	0.048***
	(0.004)	(0.005)	(0.003)	(0.011)	(0.012)	(0.002)

	ΔAssets$_t$	ΔSales$_t$	ΔEmployment$_t$	ΔInt. assets$_t$	ΔTan. assets$_t$	ΔProductivity$_t$
Table A2.2 continued						
Cash ratio$_{T-1}$	-0.051***	-0.057***	0.072***	-0.006	0.151***	-0.030***
	(0.008)	(0.010)	(0.008)	(0.034)	(0.027)	(0.004)
Age	0.069***	0.022***	0.053***	-0.180***	-0.011	0.002
	(0.005)	(0.007)	(0.006)	(0.027)	(0.016)	(0.002)
Constant	3.582***	3.912***	2.273***	-2.047***	1.111***	0.063***
	(0.037)	(0.055)	(0.042)	(0.165)	(0.104)	(0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**291,315**	**290,991**	**290,300**	**290,331**	**290,791**	**289,885**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff panel estimates on year-on-year growth in total assets, sales, employment cost, intangible fixed assets, tangible fixed assets and labour productivity (Sales to employment cost). Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using PSM (1:1 ratio, nearest neighbor). Gloan is an indicator variable equal to one for beneficiaries from the signature year. All models include fixed effects by firm and year. Robust standard errors in round brackets.

References

- Almeida, H., Campello, M. (2007). “Financial Constraints, Asset Tangibility, and Corporate Investment”. The Review of Financial Studies, Volume 20, Issue 5, September 2007, Pages 1429–1460.

- Asdrubali, P. and S. Signore (2015), “The Economic Impact of EU Guarantees on Credit to SMEs – Evidence from CESEE Countries”. EIF Working Paper No. 2015/29.

- Berger, A. N., and Udell, G. F. (1998). “The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle”. Journal of Banking & Finance, 22(6–8), Pages 613–673.

- Bertoni, F., Brault, J., Colombo, M.G., Quas, A. and S. Signore (2019). “Econometric study on the impact of EU loan guarantee financial instruments on growth and jobs of SMEs”. EIF Working Paper No. 2019/54.

- Bertoni, F., Colombo, M.G. and A. Quas (2023). “The long-term effects of loan guarantees on SME performance”. Journal of Corporate Finance 80, 102408.

- Blundell, R., Costa Dias, M., Meghir, C., and J. van Reenen (2004). “Evaluating the Employment Impact of a Mandatory Job Search Program”. Journal of the European Economic Association, Volume 2, Issue 4, 1 June 2004, Pages 569–606.

- Brault, J. and S. Signore (2019). “The real effects of EU loan guarantee schemes for SMEs: A pan-European assessment”. EIF Working Paper No. 2019/56.

- Cox, D. (1972). “Regression models and life-tables”. Journal of the Royal Statistics Society. 34, 187–220.

- Esho, E., Verhoef, G. (2018). “The funding gap and the financing of small and medium businesses: An integrated literature review and an agenda”. MPRA Paper, (90153).

- Heckman, J. J. (1979). “Sample Selection Bias as a Specification Error”. Econometrica, 47(1), 153–161.

- Heckman, J.J., Ichimura, H., Todd, P.E. (1997). “Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme”. The Review of Economic Studies, Volume 64, Issue 4, October 1997, Pages 605–654.

- Kraemer-Eis, H., Botsari, A., Gvetadze, S., Lang, F., and Torfs, W. (2018). European Small Business Finance Outlook, June 2018. EIF Working Paper No. 2018/50.

- Kremp, E. and Sevestre P. (2013). “Did the crisis induce credit rationing for French SMEs?” Journal of Banking & Finance, 37(10), 3757–3772.

- Lechner, M. (2010). “The Estimation of Causal Effects by Difference-in-Difference Methods Estimation of Spatial Panels”. Foundations and Trends in Econometrics, 4(3), 165–224.

- Sinnott, E, Gatti M. and van der Wielen W. (2023), “Impact assessment of the EIB’s intermediated lending to businesses”, European Investment Bank.

About

… the European Investment Fund

The European Investment Fund (EIF) is Europe's leading risk finance provider for small and medium sized enterprises (SMEs) and mid-caps, with a central mission to facilitate their access to finance. As part of the European Investment Bank (EIB) Group, the EIF designs, promotes and implements equity and debt financial instruments which specifically target the needs of these market segments.

In this role, the EIF fosters EU objectives in support of innovation, research and development, entrepreneurship, growth, and employment. The EIF manages resources on behalf of the EIB, the European Commission, national and regional authorities and other third parties. The EIF support to enterprises is provided through a wide range of selected financial intermediaries across Europe. The EIF is a public-private partnership whose tripartite shareholding structure includes the EIB, the European Union represented by the European Commission and various public and private financial institutions from European Union Member States, the United Kingdom and Turkey. For further information, please visit www.eif.org.

… EIF's Impact Assessment

The Impact Assessment division supports the EIF's transition to an impact-driven institution by designing and implementing a comprehensive Impact Assessment Framework. In this context, rigorous ex-post impact studies, typically based on large-scale micro-data and advanced econometric methods, are crucial for analysing and understanding the medium- to long-term outcomes of the EIF's activities.

… this Working Paper series

The EIF Working Papers are designed to make available to a wider readership selected topics and studies in relation to EIF´s business. The Working Papers are edited by EIF´s Market Assessment & Research and Impact Assessment divisions and are typically authored or co-authored by EIF staff, or written in cooperation with the EIF. The Working Papers are usually available only in English and distributed in electronic form (pdf).

EIF Working Papers

2025/103	Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania
2024/102	EIF Private Equity Mid-Market Survey 2024: Market sentiment
2024/101	European Small Business Finance Outlook 2024
2024/100	Skills in European entrepreneurial finance
2024/099	EIF Venture Capital Survey 2024: Market sentiment
2024/098	Cleantech Industry Survey 2023 Financing, regulatory, innovation and human capital issues
2024/097	Addressing Financial and Digital Literacy Challenges for Inclusive Finance: Insights from Microfinance Institutions and FinTech Organisations.
2023/096	European Small Business Finance Outlook 2023.
2023/095	EIF Private Equity Mid-Market Survey 2023: Market sentiment, scale-up financing and human capital.
2023/094	Open banking and inclusive finance in the European Union: perspectives from the Dutch stakeholder ecosystem
2023/093	EIF Venture Capital Survey 2023
2023/092	The 2022 EIF SME Access to Finance Index – August 2023 update
2023/091	Using machine learning to map the European Cleantech sector
2023/090	Recent trends in EU corporate demography and policy
2023/089	Entrepreneurial Finance and the Russian War against Ukraine: a Survey of European Venture Capital and Private Equity Investors
2023/088	Fairness in algorithmic decision systems: a microfinance perspective
2023/087	Female access to finance: a survey of literature.
2023/086	Determinants of EU Greentech investments: the role of financial market conditions.
2022/085	EIF Private Equity Mid-Market Survey 2022: Market sentiment and impact of the current geopolitical & macroeconomic environment.
2022/084	European Small Business Finance Outlook 2022.
2022/083	The 2021 EIF SME Access to Finance Index. October 2022 update.
2022/082	EIF VC Survey 2022: Market sentiment and impact of the current geopolitical & macroeconomic environment.
2022/081	EIF Business Angel Survey 2021/22: Market sentiment.
2022/080	EIF Private Debt Survey 2021 - ESG considerations in the lending strategy of private debt funds.
2022/079	EIF Private Debt Survey 2021 - Private Debt for SMEs - Market overview.
2021/078	EIF Private Equity Mid-Market Survey 2021: Market sentiment.

2021/077	EIF Private Equity Mid-Market Survey: Fund managers' perception of EIF's value added.
2021/076	The 2020 EIF SME Access to Finance Index - October 2021 update.
2021/075	European Small Business Finance Outlook.
2021/074	EIF Venture Capital Survey 2021: Market sentiment.
2021/073	EIF VC Survey Autumn 2020 - Regional analysis.
2021/072	Financial and social inclusion in Europe.
2021/071	EIF Venture Capital, Private Equity Mid-Market & Business Angels Surveys 2020: Market sentiment – COVID-19 impact – Policy measures.
2021/070	The impact of VC on the exit and innovation outcomes of EIF-backed start-ups.
2021/069	Scale-Up Financing and IPOs: Evidence From Three Surveys.
2020/068	The EIF SME Access to Finance Index - September 2020 update.
2020/067	European Small Business Finance Outlook 2020. The impact of COVID-19 on SME Financing markets.
2020/066	Measuring microfinance impact: A practitioner perspective and working methodology.
2020/065	The social return on investment (SROI) of four microfinance projects.
2020/064	The market sentiment in European Private Equity and Venture Capital: Impact of COVID-19.
2020/063	ESG considerations in Venture Capital and Business Angel investment decisions: Evidence from two pan-European surveys.
2020/062	The Business Angel portfolio under the European Angels Fund: An empirical analysis.
2019/061	European Small Business Finance Outlook.
2019/060	EIF Business Angels Survey 2019 - Market sentiment, public intervention and EIF's value added.
2019/059	EIF VC Survey 2019 - Fund managers' market sentiment and policy recommendations.
2019/058	EIF SME Access to Finance Index – June 2019 update.
2019/057	European Small Business Finance Outlook.
2019/056	The real effects of EU loan guarantee schemes for SMEs: A pan-European assessment.
2019/055	The European Venture Capital Landscape: an EIF perspective. Volume V: The economic impact of VC investments supported by the EIF.
2019/054	Econometric study on the impact of EU loan guarantee financial instruments on growth and jobs of SMEs.
2018/053	European Small Business Finance Outlook.
2018/052	The effects of EU-funded guarantee instruments of the performance of Small and Medium

	Enterprises - Evidence from France.
2018/051	EIF VC Survey 2018 - Fund managers' perception of EIF's Value Added.
2018/050	European Small Business Finance Outlook.
2018/049	EIF SME Access to Finance Index – June 2018 update.
2018/048	EIF VC Survey 2018 – Fund managers' market sentiment and views on public intervention.
2018/047	EIF SME Access to Finance Index.
2017/046	European Small Business Finance Outlook.
2017/045	The European venture capital landscape: an EIF perspective. Volume IV: The value of innovation for EIF-backed startups.
2017/044	Financing Micro Firms in Europe: An Empirical Analysis.
2017/043	European Small Business Finance Outlook.
2017/042	Credit Guarantee Schemes for SME lending in Western Europe.
2017/041	The European Venture Capital landscape: an EIF perspective. Volume III: Liquidity events and returns of EIF-backed VC investments.
2017/040	Financing Patterns of European SMEs Revisited: An Updated Empirical Taxonomy and Determinants of SME Financing Clusters.
2017/039	Guaranteeing Social Enterprises – The EaSI way.
2016/038	The European Venture Capital Landscape: an EIF perspective. Volume II: Growth patterns of EIF-backed startups.
2016/037	European Small Business Finance Outlook.
2016/036	The role of cooperative banks and smaller institutions for the financing of SMEs and small midcaps in Europe.
2016/035	European Small Business Finance Outlook.
2016/034	The European Venture Capital Landscape: an EIF perspective. Volume I: the impact of EIF on the VC ecosystem.
2016/033	Evaluating the impact of European microfinance. The foundations.
2015/032	European Small Business Finance Outlook.
2015/031	SME Securitisation – at a crossroads?
2015/030	Financing patterns of European SMEs: An Empirical Taxonomy.
2015/029	The Economic Impact of EU Guarantees on Credit to SMEs - Evidence from CESEE Countries.
2015/028	European Small Business Finance Outlook.
2015/027	Bridging the university funding gap: determinants and consequences of university seed funds and proof-of-concept Programs in Europe.
2014/026	European Small Business Finance Outlook.
2014/025	Institutional non-bank lending and the role of debt funds.
2014/024	European Small Business Finance Outlook.
2014/023	Pricing Default Risk: the Good, the Bad, and the Anomaly.
2014/022	Guidelines for SME Access to Finance Market Assessments.

2014/021	Financing the mobility of students in European higher education.
2013/020	European Small Business Finance Outlook.
2013/019	SME loan securitisation 2.0 – Market assessment and policy options.
2013/018	European Small Business Finance Outlook.
2013/017	Forecasting distress in European SME portfolios.
2012/016	European Small Business Finance Outlook.
2012/015	The importance of leasing for SME finance.
2012/014	European Small Business Finance Outlook.
2012/013	Progress for microfinance in Europe.
2011/012	European Small Business Finance Outlook 2/2011.
2011/011	Business Angels in Germany. EIF's initiative to support the non-institutional financing market.
2011/010	European Small Business Finance Outlook.
2011/009	The performance and prospects of European Venture Capital.
2010/008	Impact of Legislation on Credit Risk – How different are the U.K. and Germany?
2010/007	SME Loan Securitisation – an important tool to support European SME lending.
2010/006	Drivers of Private Equity Investment activity. Are Buyout and Venture investors really so different?
2010/005	Private Equity Market Outlook.
2010/004	Private Equity and Venture Capital Indicators – A research of EU-27 Private Equity and Venture Capital Markets.
2010/003	Private Equity Market in Europe – Rise of a new cycle or tail of the recession?
2009/002	Financing Technology Transfer.
2009/001	Microfinance in Europe – A market overview.

European Investment Fund

Scan below to obtain a PDF version of this working paper

Follow our stories and work

European Investment Fund

@eif4smes

@EIF_EU

engage.eif.org