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Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Belgium, France and Italy

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Preface

Small and Medium-sized Enterprises (SMEs) are the lifeblood of the EU economy. Yet, unlike their larger counterparts, they often struggle to access finance. These difficulties stem from persistent frictions and/or other imperfections in credit markets (Esho and Verhoef, 2018).

To counter these market gaps, governments and institutions at both the national and EU level have put in place financial measures to support SME lending - chief among them Public Credit Guarantee Schemes (CGSs). By alleviating lenders' risk, CGSs boost banks' lending capacity, thereby opening up more debt financing opportunities for SMEs (Kraemer-Eis et al., 2018).

One of the cornerstones in this effort is the EU's SME guarantee system, funded by the EU and managed by the EIF. Over several decades, this policy tool has evolved in step with the European Commission's programming cycles. Today, under the "InvestEU" programme (2021–2027), the EIF is deploying EUR 10bn in EU SME guarantees.

But for the EIF, success is not solely about volumes. The real objective lies in delivering meaningful impact for SMEs. That is why assessing the results of EIF's activities is so important. With guarantee schemes now widely used across Europe, there is also rising demand to better understand their economic effects.

Ex-post impact assessments – typically built on large-scale micro-data – are key for analysing the medium- and long-term outcomes of CGSs. Yet they come with their own set of challenges, most notably the problem of establishing causality.

In recent years, the EIF has built a strong track record in assessing the impact of policies that support SME financing, from guarantees to equity schemes. These studies – published in the EIF Working Paper series – apply sophisticated econometric methods and benefit from collaboration with leading academics, which strengthens both their credibility and independence.

This latest analysis focuses on the COSME Loan Guarantee Facility, extending the scope of earlier assessments of its predecessors (MAP/CIP). By broadening the geographical reach, the paper paints a more detailed picture of the EU market landscape and sheds light on how EU-level guarantees work across diverse national settings.

Looking ahead, the EIF is committed to refine its impact assessment approach even further, including to explore new ways to sharpen its methodological tools. Ex-post impact studies are a key part of our ongoing work to design and implement a comprehensive Impact and Additionality Assessment Framework. In this context, they provide not only valuable retrospective insights, but also crucial information to anticipate the results and impact of future support initiatives, thereby promoting the continuous improvement of the EIF's operations.

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Executive Summary[1]

In this report, we present the results of the analysis of the treatment effect of the COSME loan guarantee facility (LGF) in three European countries (Belgium, France, and Italy) during 2015-2023.

We estimated 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 transaction year), and fixed-effect panel data models. We also resorted to probit and Cox proportional-hazard models to estimate the treatment effect on the survival of guaranteed-loan beneficiaries.

Our main findings showed that three years after the beginning of the transaction year, beneficiaries outgrew matched companies. The additional logarithmic (percentage) growth was 8.0 percentage points (p.p.) for assets, 5.4 p.p. for sales, 7.8 p.p. for employment, 52.3 p.p. for intangible fixed assets, and 24.7 p.p. for tangible fixed assets. Labour productivity increased in beneficiaries by 0.234 less than in matched companies (which corresponds to approximately 2% of the pre-treatment level). All these estimates were statistically significant at the 1% level.

These effects are similar to those identified in the previous studies but with important differences. With respect to our previous COSME assessment, results tend to be smaller, confirming that the effectiveness of COSME strongly depends on the national contexts. With respect to the studies focusing on MAP and CIP, they are quite similar to the study based on French beneficiaries (Bertoni et al., 2023) but smaller than those reported in Bertoni et al. (2019) for companies in Benelux, Italy, and Nordic countries.

As in previous studies, we investigated how company-specific characteristics influenced the treatment size. The treatment effect is generally larger for smaller and younger companies. In fact, excluding firms under two years due to missing data may understate this effect, which could be stronger if this more financially constrained subgroup were observable. The results were robust to changes in the matching method, the inclusion of additional controls, adjustment for inflation, and control (in a panel setting) for unobserved time-invariant differences between treated and control-group companies.

We also considered companies experiencing a credit uptake. We define a credit uptake as a yearly increase in the amount of loans that results in an increase of at least 5 percentage points in a firm’s leverage ratio (loans to total assets). In other words, it captures cases where firms substantially expand their use of external credit, rather than changes driven mainly by asset contraction. Moreover, we distinguish these firms based on whether the credit uptake was associated with a guaranteed loan or not. Our findings indicate that firms that experienced a credit uptake generally grew faster than firms that did not, at least for some aspects (employment, intangible assets, and tangible assets). However, firms that received a guaranteed loan that did not qualify as a credit

[1] This report benefitted from the comments and input of many EIF colleagues, for which we are very grateful. In particular we would like to acknowledge the invaluable help of our Impact Assessment colleagues Camila Carlos Ballerini, Andrea Crisanti and Elena Stasi. Moreover, we are thankful to Luís Broegas Amaro for the useful support and review.

uptake grew significantly more than matched firms that did not experience credit uptakes. In other words, even relatively small guaranteed loans had a significant positive effect on their beneficiaries. In addition, the combined effect of receiving a guaranteed loan and a credit uptake in the same year had a positive and significant effect on growth in total assets and an effect that was negative but insignificant on other growth measures.

Regarding survival, beneficiaries of guaranteed loans were 6.8 percentage points less likely than matched companies to go bankrupt by the end of 2024.

These results confirm that guaranteed loans are associated with substantial growth of the beneficiaries, in line with the COSME objective of improving access to finance for SMEs that would otherwise be credit-constrained. From a policy perspective, it is also important to point out that guaranteed loans do not cause unwanted effects, like an increase in firms' failure rate or a drastic and persistent drop in firms' long-term labour productivity, and that when they lead to a substantial increase in firms' leverage, they have more positive effects on asset growth than regular (i.e., non-guaranteed) loans. This latter result points to the additionality of COSME guarantees.

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1 Introduction

In this report, we present the results of the analysis of the treatment effect of the COSME loan guarantee facility (LGF) in three European countries (Belgium, France, and Italy) from 2015 to 2024.

The COSME LGF is the latest of a series of guaranteed-loan programs implemented by the EIF, including the Multiannual Programme for Enterprises (MAP) from 2001 to 2005 and the Competitiveness and Innovation Framework Programme (CIP) from 2007 to 2013.

Through these programmes, 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.

Several studies have explored EIF-backed guaranteed loan programmes. 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 receiving 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 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 found that, over a 5-year horizon, and again compared to matched companies, sales increase in logarithms (percentage) by 0.0656 (6.8 percentage points (p.p.)), employment cost by 0.0689 (7.1 p.p.), and assets by 0.0672 (7.0 p.p.). The authors found 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 found that over the three years after the beginning of the transaction 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) provided a pan-European assessment of EU MAP and CIP programmes from 2002 to 2016. They found that guaranteed loans positively affected 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 found that beneficiaries had lower bankruptcy rates than matched firms.

In a previous study "Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania"[2], we extended these findings to a different EIF guarantee programme (COSME LGF), a more recent period (2015-2023), and the following countries: Greece, Poland, Romania, and Spain. In this study, we update the analysis based on three additional countries: Belgium, France, and Italy.

Similarly to previous programmes, COSME guarantees target SMEs, which experience well-known difficulties in accessing credit 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 the 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, transaction years, and countries.

COSME guarantees are provided to companies in each country by selected financial intermediaries, typically large banking groups. EIF signs a specific contract with each local financial intermediary that has applied and been selected.. Among others, the contracts define the characteristics of the target group and of the guarantees, as well as the expected number of transactions. These characteristics might influence the guarantees' effectiveness.

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 bad 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.

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, and the presence of counter-guarantees. Again, the effectiveness of COSME guarantees could vary across these characteristics. Most notably, guarantees meant to finance long-term investments are expected to favour companies' growth in tangible and intangible assets. Instead, guarantees targeted to 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[3].

The COSME guaranteed loans often imply the further benefit for companies of lowering or neutralizing collateral requirements for loans. In this way, they particularly benefit younger firms with low asset tangibility, facilitating their access to capital despite a lack of collateral.

Our main findings confirm the positive impact of COSME guaranteed loans. Beneficiaries outgrew matched companies three years after the beginning of the transaction year. The additional

[2] EIF Working Paper 2025/103, Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania

[3] It is worth noting that, during the COVID-19 pandemic, the probability of receiving some form of financial support was higher for all firms. Since our control group was constructed to reflect comparable firms, this does not compromise our identification strategy. However, the widespread availability of alternative support measures may imply that our estimates represent a lower bound of the true effect of COSME guarantees on beneficiaries' financial performance.

logarithmic (percentage) growth is 0.067 (8.0 p.p.) in assets, 0.053 (5.4 p.p.) in sales, 0.075 (7.8 p.p.) in employment, 0.421 (52.3 p.p.) in intangible fixed assets, and 0.221 (24.7 p.p.) in tangible fixed assets. All these estimates are statistically significant at the 1% level. Labour productivity, measured by the ratio of sales to employment costs, decreased over the 3-year time horizon by 23.4 cents of sales for each Euro of employment cost, mostly due to the faster increase in employment cost with respect to sales. This decrease corresponds to approximately 2% of the pre-treatment level.

These effects are similar to those identified in the previous studies but with important differences. With respect to the very recent and virtually identical COSME exercise, they tend to be smaller, confirming that the effectiveness of COSME strongly depends on the national contexts. With respect to the studies focusing on MAP and CIP, they are quite similar to the study based on French beneficiaries (Bertoni et al., 2023) but smaller than those reported in Bertoni et al. (2019) for companies in Benelux, Italy, and Nordic countries. The specificities of the involved financial intermediaries, the design of the programmes, or changes in the macroeconomic context might explain these differences. Moreover, it is worth mentioning the significant increase in the use of credit guarantees in the three target countries in the most recent years (OECD, 2021), which might have, to some extent, influenced their effectiveness.

As in previous studies, we investigate how company-specific characteristics influence the treatment magnitude. The treatment effect was generally larger for smaller and younger companies. The results are robust to changes in the matching method, the inclusion of additional controls, adjustment for inflation, and control (in a panel setting) for unobserved time-invariant differences between treated and control-group companies.

We also considered companies experiencing a credit uptake. We define a credit uptake as a yearly increase in the amount of loans that results in an increase of at least 5 percentage points in a firm's leverage ratio (loans to total assets). In other words, it captures cases where firms substantially expand their use of external credit, rather than changes driven mainly by asset contraction. Moreover, we distinguish these firms based on whether the credit uptake was associated with a guaranteed loan or not. Our findings indicate that firms that experienced a credit uptake generally grew faster than firms that did not, at least for some aspects (employment, intangible assets, tangible assets). However, firms that received a guaranteed loan that did not qualify as a credit uptake grew significantly more than matched firms that did not experience credit uptakes. In other words, even relatively small guaranteed loans had a significant positive effect on their beneficiaries. In addition, the combined effect of receiving a guaranteed loan and a credit uptake in the same year had a positive and significant effect on growth in total assets and an effect that is negative but insignificant on other growth measures. These results point to the additionality of COSME guarantees.

Regarding survival, beneficiaries were 6.8 p.p. less likely than matched companies to go bankrupt by the end of 2023, an effect which is larger than that reported in our previous COSME study but similar to that highlighted by Bertoni et al. (2023). We found a more positive effect on survival for companies with no intangible assets.

Overall, these results confirm that guaranteed loans are associated with a substantial additional growth of the beneficiaries. Beneficiaries also invest substantially more in tangible and, more interestingly, intangible fixed assets. This latter result is relatively rare in the 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 an increase in firms' failure rate. A point of attention is the drop in labour productivity, which is, however, mostly focused on the short term.

The rest of this report is organized as follows. In Section 2, we present the methodology we use 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 conclude.

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 3.2);
- 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[4] 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[5].

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 adopted 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 between the

[4] Winsorization is the process of limiting extreme values in a distribution by replacing observations below (above) a chosen percentile with the value at that percentile. Here, growth measures are winsorized at the 1st and 99th percentiles to reduce the influence of outliers while retaining all observations.

[5] 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).

treated and control companies after the treatment and subtract the outcome difference that had been there already before the treatment had any effect (conditional on controls). The diff-in-diff methodology 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 checked that treated and untreated observations had the same trends in terms of assets, sales, cost of employees, and intangible and tangible fixed assets before the treatment.

We used both cross-section and panel diff-in-diff specifications for our growth models.

In a cross-section setting, we used one observation for each treated and untreated company. We analysed how companies grew between T-1 (the beginning of the transaction year) and T+2 (the end of the second year after the transaction year). For instance, for a company that received a guaranteed loan in June 2016, we studied its growth between Dec 31, 2015, and Dec 31, 2018. We decided to focus on this time horizon mainly because of data availability issues and to ensure comparability with previous studies. We used the following cross-section specification for our diff-in-diff growth model:

$$D_3Y_T = Y_{T+2} - Y_{T-1} = \beta_0 + \beta_1 Y_{T-1} + \beta_2 D_1 Y_{T-1} + \beta_3 GLoan + \gamma X_{T-1} + \mu_T + s + c + \epsilon$$

Where $D_3Y_T = Y_{T+2} - Y_{T-1}$ 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 captures how much such growth for treated companies is higher or lower than the growth of untreated companies over the same period and represents our diff-in-diff estimator.

The models control for companies' characteristics before the transaction year (Y_{T-1}) and for their lagged growth ($D_1Y_{T-1} = Y_{T-1} - Y_{T-2}$). 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 controlled 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[6] 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. Moreover, we control for transaction year (μ_T), sector (s), and country (c) fixed effects.

As shown in the following, we conducted several robustness checks for our model specification, including considering different horizons for the treatment beyond T+2.

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

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

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

In this case, the dependent variables represented companies' annual growth in total assets, sales, employment cost, tangible and intangible assets and labour productivity. The two-way fixed effects models included company (w_i) and time (μ_T) fixed effects. The step variable *GLoan* switched 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 was the companies' survival. Again, we adopted a counterfactual approach, although the control group was slightly different, as explained in Section 3.2.

We adopted two alternative specifications to model the survival of treated and untreated companies. First, we simply tested whether treated companies were more or less likely than untreated companies to fail up to 2024, 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 used probit models in which regressors are the same as the ones used in the cross-section growth models. The coefficient of the *GLoan* dummy captures differences in the failure likelihood across treated and untread companies.

Second, we exploited the information on when the company failed. We used 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 on not having failed till that moment. The exposure time is the number of years since the transaction year and 2024 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 were identical to the probit specification, and again the coefficient of *GLoan* captured differences in the hazard rates of failing across treated and untread companies.

2.2.3 Power analysis

Before identifying the control group, we conducted a power analysis to determine the necessary sample size to study the phenomenon. The objective was to identify the order of magnitude of the sample size that we need to identify the effect of guaranteed loans reasonably.

In this report, we looked at the treatment effect of guaranteed loans over different periods (2-4 years) and dependent variables (total assets, sales, employment, intangible fixed assets, tangible fixed assets, and labour productivity) and using several different 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 was to give us a ballpark estimate of the sample size that we need to study the phenomenon, we instead conducted the power analysis on a (hopefully representative) setting: the cross-sectional estimate of the treatment effect of guaranteed loans on firm's sales with a 3-year time horizon and using 1:1 PSM.

The power analysis studies the relationship between

- the power of a test ($1-\beta$);
- the sample size (N);
- the level of significance (α);
- the non-center parameter (δ, which is the extent to which the null hypothesis is false).

Here we wanted to calculate the sample size N given the other parameters.

To set δ, we started from the estimates present in our previous COSME report. The 3-year logarithmic growth in sales is 0.0406 (with a standard deviation of 0.8356) in the 1:1 matched control group and 0.1349 (with a standard deviation of 0.7816) for guaranteed-loan beneficiaries. This difference of 0.0895 (with a standard deviation of 0.8094) is a diff-in-diff unconditional estimate of the 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 4,386 units, which (because of 1:1 PSM) means 2,193 treated companies. In other words, if the true treatment effect in this study were of similar size as the one estimated in the previous COSME study, a sample of 2,193 beneficiaries would give us a 90% probability of rejecting the false null hypothesis that the treatment effect was 0 while maintaining type-I error at 1%.

Note that this number is much smaller than the total number of "usable" observations in this study (our baseline 1:1 regression includes 172,000 observations). 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 year, age classes, and industry (with the exception of industry AB, in which the number of treated units falls below the threshold).

The only breakdown that results in a number of observations that is substantially below the threshold is the one by country because, as discussed later, of the size of the Belgian subsample. In our main treatment effect analysis, we only had 756 usable observations for Belgium. We should then expect large confidence intervals for this country and a lower probability of rejecting the null hypothesis even when it is false. If we assume that the order of magnitude of the phenomenon is similar to that observed in our latest COSME report, the power of the analysis would be only 37.7%. In summary, non-significant results on the Belgian subsample could be due to the analysis's limited power caused by the sample's numerosity.

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3 Data

3.1 Population of treated companies

In this study, the population of interest consisted of all companies that received COSME-guaranteed loans in the period 2015-2023 in Belgium, France, and Italy. Occasionally, companies might receive more than one COSME guaranteed loan during this period and even more than one loan per year. Because performance is measured using accounting data, which naturally has annual frequency, the unit of analysis is not the individual loan but the company-transaction 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".

The population of COSME-guaranteed loans in the period 2015-2023, in Belgium, France, and Italy, as fetched by the EIF in October 2024, corresponded to 581,365 loans granted to 460,272 companies.

Table 1 shows the distribution of the population by country and transaction year. Most loans were granted to French (56.56%) and Italian (42.42%) companies, while a minority of loans (1.01%) to Belgian companies. The distribution across years indicates a peak of activity in 2020 and 2021 for Belgium, in 2019 for France, and in 2018 and 2020 for Italy, with a much lower number of loans in 2015 and in more recent years. The distribution of loans in Belgium was quite significant in 2022 and 2023 (more than 10% of the total number of loans in each year), with a few loans granted in 2024 (0.95%). In France, 2023 was the last transaction year, with 4.36% of the loans. In Italy, the distribution virtually stopped in 2021 with 5.45% of the loans granted, while less than 1% of loans were granted in 2022 and 2023.

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

	Belgium		France		Italy		Total	
	N	Col%	N	Col%	N	Col%	N	Col%
2015	79	1.34	17,109	5.20	6,757	2.74	23,945	4.12
2016	378	6.41	35,448	10.78	24,086	9.77	59,912	10.31
2017	354	6.00	40,148	12.21	42,844	17.37	83,346	14.34
2018	618	10.48	40,643	12.36	61,220	24.82	102,481	17.63
2019	698	11.84	51,466	15.65	32,421	13.15	84,585	14.55
2020	1,257	21.32	43,788	13.32	64,546	26.17	109,591	18.85
2021	1,200	20.35	42,048	12.79	13,450	5.45	56,698	9.75
2022	619	10.50	43,853	13.34	1,015	0.41	45,487	7.82
2023	636	10.79	14,340	4.36	287	0.12	15,263	2.63
2024	57	0.97	n.a.	n.a.	n.a.	n.a.	57	0.01
Total	**5,896**	**100**	**328,843**	**100**	**246,626**	**100**	**581,365**	**100**

3.2 Sample construction

As accounting data were not available for all firms and years, the econometric study was 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' fiscal code(s), names, city, and country. Overall, after removing duplicates, only 484,904 loans, corresponding to 83.06% of the original population, had a corresponding 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 Belgium was the lowest (59.40%), while better matching rates were found for France (75.22%) and Italy (94.04%). In terms of transaction years, the coverage is extremely high for loans granted in the 2015-2020 period (around 97%), around 30% for 2021, 2022 and 2023, and as low as 5.26% for the few loans granted in 2024.

Our sample was 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 needed both information before the treatment (in T-2 and T-1) and after (T+2).

We analysed 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 transaction year and in the transaction year itself, accounting data on the beneficiaries' total assets, sales, and cost of employees, were available for less than half of the loans associated with a BvD ID code. For turnover, we had 209,540 useful data points in T (43.39% of the 484,904 loans) and 169,011 data points (38.62%) in T-1. The incidence of missing information increased as we moved forward from the transaction year, and turnover information is available only for 20.09% of observations in T+3 and 7.72% of observations in T+5. For other variables, the incidence of missing values was generally higher. The availability of data for tangible and intangible fixed assets was virtually identical to the one on total assets.

In Figure 2, we analyse data availability by country. Italy had overall the best coverage, in terms of total assets (48.2%), turnover (61.9%), and employment cost (45.1%). In France, coverage is 20.5% for total assets, 26.5% for turnover, and 13.4% for employment cost. In Belgium, data on total assets and employment were fairly available (48.6% and 36.6%, respectively). However, data on turnover were virtually always missing (they were available only for 4.8% of loans). For this reason, we decided to exclude Belgium from the analysis of the impact of loans on turnover.

In preparation for the following steps, we decided first to exclude companies without total assets in T-1. At this stage, we also included 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);
- Companies with negative values of total assets in T-1;

- Loans granted since 2022, because of the almost systematic unavailability of data in the post-treatment period for these loans;
- Companies treated in the foundation year, because of the unreliability of accounting data in these cases;
- Companies without industry NACE codes in Orbis.

These exclusions resulted in a sample of 159,707 loans, corresponding to 33.07% of the original population and described in Column III of Table 2. We used this sample for the extraction grid described in Section 3.3.1.

Second, we excluded companies without full accounting measures in T-2 and T-1. Besides total assets, we also required the availability of sales, cost of employees and tangible and intangible fixed assets in T-1 and T-2 (needed to compute growth measures), and equity value (“shareholder funds” in Orbis) and cash and cash equivalents in T-1. We used the latter two measures to compute control variables for leverage and liquidity. For Belgium, we relaxed the requirement of the availability of sales in T-2 and T-1.

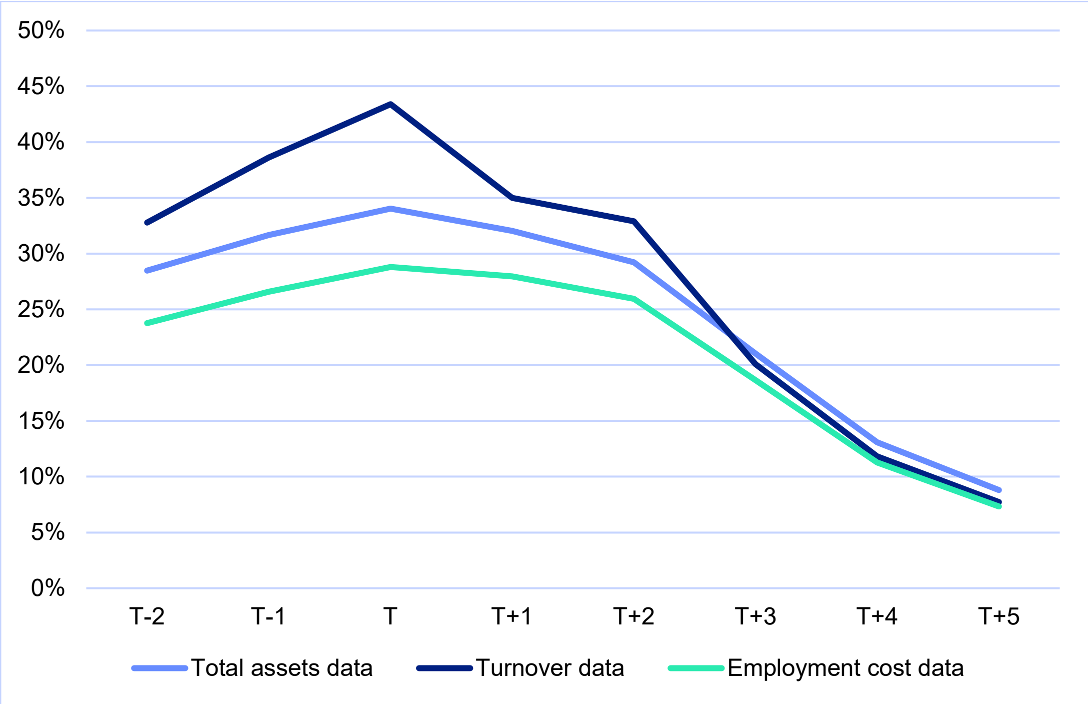
We used the resulting sample of 111,659 loans (23.12% of the original population) in the survival analysis described in Section 4.3. We report the distribution of this sample by country and transaction year in Column IV of Table 2.

To carry out our growth estimates, we further excluded companies without a full set of accounting measures in T+2. In this case, we required information on the variables we used as key performance indicators, i.e., total assets, sales, cost of employees, and tangible and intangible fixed assets in T+2. We used the resulting sample of 91,717 (18.99% of the original population) in the propensity score matching described in Section 3.3.3 and the growth analyses (Section 4.1). We reported the distribution of this sample by country and transaction year in Column V of Table 2.

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

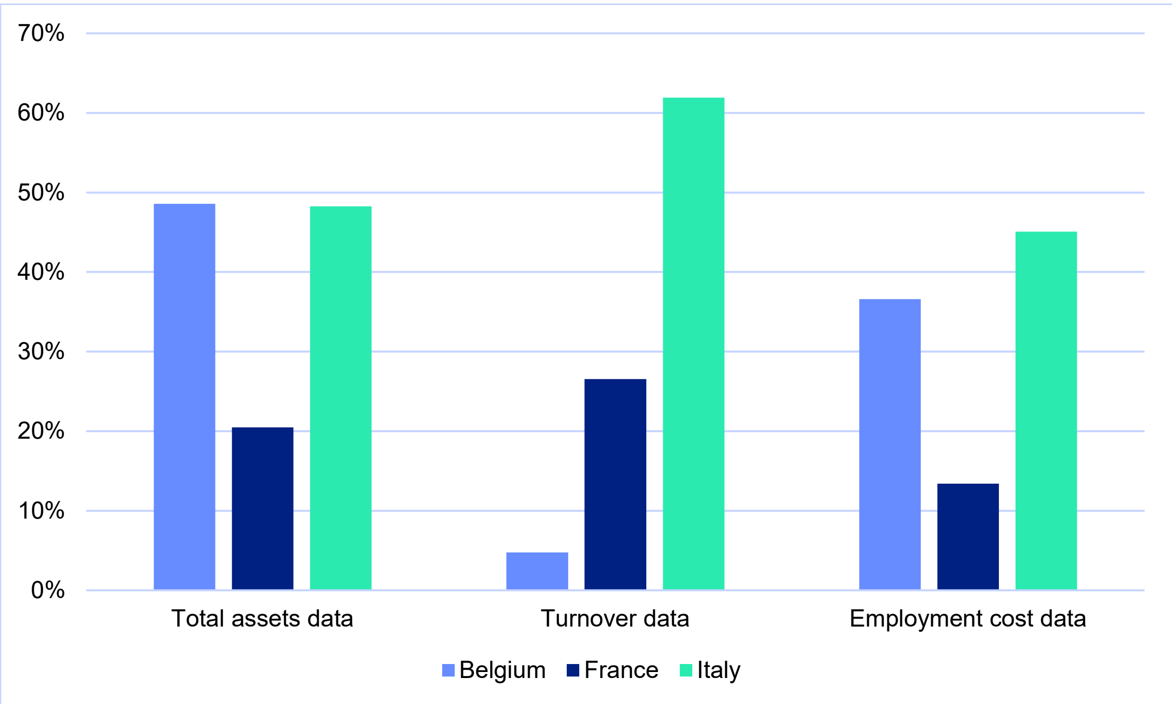
	I	II		III		IV		V	
	Total Loans (a)	Loans with BvD after removing duplicates (b)		Loans with total asset data in T-1 (used for extraction grid)		Loans with full data in T-2 and T-1 (used for survival analysis)		Loans with full data T-2, T-1 and T+2 (used for growth analysis)	
	N	N	%(a)	N	%(b)	N	%(b)	N	%(b)
Total	**581,365**	**482,904**	**83.06%**	**159,707**	**33.07%**	**111,659**	**23.12%**	**91,717**	**18.99%**
Belgium	5,896	3,502	59.40%	1,180	33.70%	756	21.59%	649	18.53%
France	328,900	247,345	75.22%	49,874	20.16%	20,591	8.32%	11,009	4.45%
Italy	246,626	232,057	94.09%	108,653	46.82%	90,312	38.92%	80,059	34.50%
2015	23,945	23,247	97.08%	6,845	29.44%	4,535	19.51%	2,961	12.74%
2016	59,912	58,503	97.65%	16,246	27.77%	10,768	18.41%	7,733	13.22%
2017	83,346	81,796	98.14%	25,959	31.74%	17,971	21.97%	14,666	17.93%
2018	102,481	100,733	98.29%	37,750	37.48%	26,981	26.78%	23,640	23.47%
2019	84,585	82,546	97.59%	24,769	30.01%	15,885	19.24%	13,757	16.67%
2020	109,591	105,953	96.68%	42,578	40.19%	32,013	30.21%	28,639	27.03%
2021	56,698	16,395	28.92%	5,560	33.91%	3,506	21.38%	321	1.96%
2022	45,487	9,191	20.21%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2023	15,263	4,537	29.73%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2024	57	3	5.26%	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

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



The graph shows the percentage of loans for which accounting data was available, by time since or till the transaction year. Data for intangible and tangible fixed assets was very similar to the one for total assets.

Figure 2 - Data availability incidence on key performance indicators by country



The graph shows the percentage of loans for which accounting data were available, by country. Data for intangible and tangible fixed assets was very similar to the one for total assets.

3.3 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. It is worth noting that in this study, we analysed the impact of guaranteed loans on the growth and survival of companies. As mentioned in Section 3.3, we used different samples for growth and survival. For survival analysis, we only required data on growth trends before the treatment (111,659 loans, see Column IV of Table 2). For the growth analysis, we also required data in T+2 to capture growth after the treatment (91,717 loans, see Column V of Table 2).

In this section, we identify two different control groups for the survival and growth analyses. Both control groups were extracted 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 transaction year.
2. *Propensity Score Matching*: The identification of a more refined control group, which was similar to the treatment group in terms of its propensity score (i.e., the probability of receiving the treatment). Importantly, in this study, we carry out two different PSM, one for the loans used in the survival analysis and one for the loans used in the growth analysis.

3.3.1 Extraction grid

We focused on loans granted to companies for which we had 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 transaction years to the treated companies at the time of the treatment. To do so, we developed an extraction grid that included the number of treated companies that present homogeneous characteristics in each stratum, i.e., a combination of countries, age classes, industries, and transaction years.

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

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

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

- AB - Agriculture and Mining: NACE sections A and B (codes 01-09);
- CHT - 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);
- CLT - Low Tech Manufacturing: a subset of NACE section C, with the remaining NACE 2 digits (10-19, 31-32);
- F - Construction: NACE section F (codes 41-43) ;
- G - Trade: NACE section G (codes 45-47);
- KI services - 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 transaction years, we focused only on 2015-2021, due to the very low availability of data in recent years.

Considering these characteristics, the number of strata is equal to 4 (countries) times 7 (transaction years) times 5 (age classes) times 7 (industries), for a total of 980. The treated companies populated only 663 of these 980 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, equal up to 30 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 assets were available in T-1 and 2) total assets were lower than 43 million EUR.[7] In total, 3,995,408 company-year observations were downloaded in this way, corresponding to the potential control group. In Table 3a, we present the distribution of the loans with available total assets in T-1 and the potential control group by transaction year, age classes, country, and industry classes used in the extraction grid. The ratio of potential control group companies to treated observations was, on average, 25. 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.

Before ensuring comparability between the treated and control groups, we further refined both groups to identify the usable observations. We required full information on turnover, total assets, and employment cost in T-1 and T-2, as well as information on cash and cash equivalent and shareholder value in T-1. This restricted the treated companies to the 111,659 sample loans described in Column IV of Table 2. With respect to the potential control group, we ended up with a sample of 2,283,681 observations.

[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.

Treated and potential control group observations with full accounting information in T-1 and T-2 are described in Table 3b. In this case, virtually all companies who were treated when they were less than 2 years old are excluded from the sample.[8]

Table 3a - Distribution of treated observations and potential control group observations with total asset data available in T-1

	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
Transaction year				
2015	6,845	192,691	199,536	28.2
2016	16,246	452,244	468,490	27.8
2017	25,959	694,953	720,912	26.8
2018	37,750	880,660	918,410	23.3
2019	24,769	670,652	695,421	27.1
2020	42,578	952,104	994,682	22.4
2021	5,560	152,104	157,664	27.4
Age classes				
1 year old	6,550	183,951	190,501	28.1
2-4 years old	28,297	752,014	780,311	26.6
5-9 years old	39,236	957,158	996,394	24.4
10-19 years old	44,693	1,103,516	1,148,209	24.7
More than 19 years old	40,922	998,769	1,039,691	24.4
Country				
Belgium	1,180	35,176	36,356	29.8
France	49,874	1,408,329	1,458,203	28.2
Italy	108,653	2,551,903	2,660,556	23.5
Industry				
AB	1,642	47,443	49,085	28.9
CHT	21,167	395,323	416,490	18.7
CLT	15,269	301,217	316,486	19.7
F	26,196	721,014	747,210	27.5
G	40,421	956,755	997,176	23.7
KI services	20,581	593,639	614,220	28.8
Other services	34,431	980,017	1,014,448	28.5
Total	**159,707**	**3,995,408**	**4,155,115**	**25.0**

[8] Table 3b includes potential control group companies which are younger than 2 years old. However, 97.7% of them are dropped in the subsequent matching processes.

Table 3b - Distribution of treated observations and potential control group observations with full data available in T-1 and T-2

	Treated (T) with full data in T-1 and T-2	Potential control group (PCG) with full data in T-1 and T-2	Total (T+PCG)	PCG/T
Transaction year				
2015	4,535	132,235	136,770	29.2
2016	10,768	288,802	299,570	26.8
2017	17,971	418,624	436,595	23.3
2018	26,981	485,029	512,010	18.0
2019	15,885	372,293	388,178	23.4
2020	32,013	502,088	534,101	15.7
2021	3,506	84,610	88,116	24.1
Age classes				
1 year old	1	15,206	15,207	15,206.0
2-4 years old	17,216	355,558	372,774	20.7
5-9 years old	28,698	572,910	601,608	20.0
10-19 years old	33,107	660,129	693,236	19.9
More than 19 years old	32,637	679,878	712,515	20.8
Country				
Belgium	756	12,372	13,128	16.4
France	20,591	754,424	775,015	36.6
Italy	90,312	1,516,885	1,607,197	16.8
Industry				
AB	1,209	25,624	26,833	21.2
CHT	17,956	307,606	325,562	17.1
CLT	11,946	217,584	229,530	18.2
F	16,743	383,257	400,000	22.9
G	28,916	604,316	633,232	20.9
KI services	12,949	304,830	317,779	23.5
Other services	21,940	440,464	462,404	20.1
Total	**111,659**	**2,283,681**	**2,395,340**	**20.5**

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

We further analyse the summary statistics of our variables of interest in T-1 for treated and potential control group companies in Table 4. We found that untreated companies in the potential control group tend to be younger and smaller, have slower growth rates (for assets, sales, employment cost, tangible and intangible fixed assets), higher labour productivity, lower leverage, and higher cash ratio. All the differences are statistically significant at the 5% level at least (t-tests).

Table 4 – Summary statistics of variables of interest for treated observations and potential control group observations

	All companies	Potential control group (PCG) with full data in T-1 and T-2	Treated (T) with full data in T-1 and T-2	Difference T-PCG	t-test significance
Ln(Total assets$_{T-1}$)	13.218	13.199	13.616	0.417	***
ΔLn(Total assets$_{T-1}$)	0.052	0.048	0.120	0.071	***
Ln(Sales$_{T-1}$)	13.305	13.276	13.886	0.610	***
ΔLn(Sales$_{T-1}$)	0.043	0.039	0.119	0.080	***
Ln(Emp. cost$_{T-1}$)	11.598	11.572	12.138	0.566	***
ΔLn(Emp. cost$_{T-1}$)	0.058	0.053	0.157	0.103	***
Ln(Int. assets$_{T-1}$)	6.107	6.033	7.621	1.587	***
ΔLn(Int. assets$_{T-1}$)	-0.082	-0.088	0.042	0.130	***
Ln(Tang. assets$_{T-1}$)	9.952	9.897	11.076	1.178	***
ΔLn(Tang. assets$_{T-1}$)	0.061	0.054	0.196	0.141	***
Productivity$_{T-1}$	27.470	28.421	7.993	-20.428	***
Leverage $_{T-1}$	0.725	0.722	0.785	0.063	***
Cash ratio $_{T-1}$	0.180	0.185	0.094	-0.091	***
Ln(Age$_T$)	2.427	2.427	2.433	0.006	**

3.3.2 Propensity Score Matching Propensity-score matching for companies used in the survival analysis

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

To extract such an 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 a quite 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, we are further confident that there is common support, i.e., that observations with a given set of characteristics exist both in the treatment and control group.

We first run a Propensity Score Matching on the sample of 111,659 loans described in Column IV of Table 2, for which we had full accounting information in years T-1 and T-2, and which we used in the survival analysis.

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

- For France and Italy ("fully fledged" PSM):
  - the 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.
- For Belgium ("reduced" PSM, excluding sales and labour productivity):
  - the total assets, employment cost, tangible and intangible fixed assets in T-1, taken in logarithms;
  - The logarithmic growth of total assets, 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 and cash ratio in T-1;
  - The logarithm of companies' age;
  - Nace 2-digit codes.

Matching on both levels and growth of the variables of interest ensured not only that selected untreated companies were 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 Section 2). The choice of the matching variables ensured that all matched treated and untread observations had no missing values of the variables of interest in T-1 and T-2. The drawback of this choice was that very young companies, for which information in T-2 was simply not defined, were systematically excluded from the analysis, as previously mentioned.

After running each probit model, we estimated the propensity scores and selected the five nearest neighbours of treated companies among untreated companies. The selected sample is described in Table 5a. We selected 431,706 untreated observations comparable to the 111,659 treated ones. On average, around 3,866 control group companies were selected for each treated observation.

Before testing the balancing of our matching, we checked whether using a different matching approach in France and Italy with respect to Belgium created strong imbalances in other variables. Figure A1a in the appendix shows the pre- and post-matching bias in the "fully fledged" PSM, based on the full set of matching variables, i.e., total asset, turnover, employment cost, growth of total assets, growth of turnover, growth of employment cost, productivity, leverage. and liquidity. Belgium was necessarily excluded from this exercise because of the lack of turnover data. The figure confirms a strong reduction in all variables in the post-matching with respect to the pre-matching. Figure A1b shows the sample in the "reduced" PSM, in which we only matched on total assets, employment cost, growth of total assets, growth of employment cost, leverage, and liquidity in all countries. Interestingly, the graph shows that the imbalance in turnover, productivity, and turnover growth is reduced after matching, despite the fact that these variables are not included in the matching strategy. This result makes us confident that in the Belgium sample, the matched companies are indeed quite similar also in terms of these "unobserved" variables, although we are not directly matching on them. In other terms, adopting slightly different matching strategies in France, Italy and Belgium does not compromise the comparability of results across countries.

We therefore created a matched sample in which we used the fully fledged PSM for France and Italy and the reduced PSM for Belgium. The final distribution is shown in Table 5a. We then tested the balancing of our matching along all matching variables. We show results in Table 5b. 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 were significantly different across the two groups after matching.

Table 5a - PSM for survival analysis: sample description

	Treated	Control	Total	T/C
Total	**111,659**	**431,706**	**543,365**	**3.866**
Belgium	756	2,439	3,195	3.226
France	20,591	90,630	111,221	4.401
Italy	90,312	338,637	428,949	3.750
2015	4,535	19,493	24,028	4.298
2016	10,768	44,650	55,418	4.147
2017	17,971	71,315	89,286	3.968
2018	26,981	100,970	127,951	3.742
2019	15,885	62,676	78,561	3.946
2020	32,013	118,947	150,960	3.716
2021	3,506	13,655	17,161	3.895

Table 5b - PSM for survival analysis: diagnostics and descriptives

		Treated	Control	%bias	%delta bias	t-test	p>t
Ln(Total assets$_{T-1}$)	U	13.616	13.553	4.3		11.76	***
	M	13.962	13.952	0.7	83.8	0.27	
ΔLn(Total assets$_{T-1}$)	U	0.120	0.102	5.6		16.32	***
	M	0.112	0.110	0.6	89	0.24	
Ln(Sales$_{T-1}$)	U	13.886	13.822	4.7		12.7	***
	M	13.950	13.957	-0.4	90.5	-0.17	
ΔLn(Sales$_{T-1}$)	U	0.119	0.103	3.4		9.32	***
	M	-0.065	-0.064	-0.2	93.2	-0.09	
Ln(Emp. cost$_{T-1}$)	U	12.137	12.124	0.9		2.57	**
	M	12.214	12.214	0	97.6	-0.01	
ΔLn(Emp. cost$_{T-1}$)	U	0.157	0.138	3.6		10.75	***
	M	-0.051	-0.043	-1.6	56.7	-0.58	
Ln(Int. assets$_{T-1}$)	U	7.621	7.409	4.7		13.84	***
	M	8.095	8.100	-0.1	97.5	-0.05	
ΔLn(Int. assets$_{T-1}$)	U	0.042	0.006	1.9		6.06	***
	M	0.077	0.073	0.2	89.3	0.07	
Ln(Tang. assets$_{T-1}$)	U	11.076	10.961	4.5		12.88	***
	M	11.691	11.672	0.8	83.3	0.3	
ΔLn(Tang. assets$_{T-1}$)	U	0.196	0.167	2.6		7.55	***
	M	0.215	0.221	-0.5	78.9	-0.23	
Productivity$_{T-1}$	U	7.993	7.733	3		9	***
	M	7.914	7.967	-0.6	79.8	-0.24	
Leverage $_{T-1}$	U	0.785	0.777	2.9		7.52	***
	M	0.822	0.836	-4.8	-64.9	-1.53	
Cash ratio $_{T-1}$	U	0.094	0.105	-8.3		-24.42	***
	M	0.088	0.090	-2.1	74.8	-0.93	
Ln(Age$_T$)	U	2.433	2.444	-1.2		-3.59	***
	M	2.578	2.578	0	96	0.02	

The EIF provided us with a panel dataset of accounting variables for the treated and matched control group from 2012 to 2023, which we used to identify a more refined control group to be used in the growth analysis, as described below.

3.3.3 Propensity Score matching for companies used in the growth analysis

As mentioned, we further refined the sample of treated and control group companies to be used in the growth analysis. In this case, we excluded from the analysis both treated and untreated observations for which data on assets, sales (except for Belgium), employment cost, and tangible and intangible fixed assets were not available in T+2 and for which we could not analyse growth. We describe the final sample of 91,717 treated companies in column V of Table 2.

Since this exclusion criteria substantially changes the distribution of treated companies with respect to those used in the PSM described above, we decided to run a second PSM on the subset of control group companies with data in T+2 to ensure the balancing of the variables. The matching strategy was identical to the one described above (based on levels and growth of the dependent variables, and levels of productivity, liquidity, and leverage, and without enforcing the availability of turnover data for Belgian companies), but in this case, we selected only the nearest neighbour for each treated observation. The 91,717 treated companies were matched with 81,268 untreated ones, for a ratio control on treated equal to 0.886. Results on the final sample and its balancing properties are shown in Tables 6a and 6b below.

Again, after matching, we observe a substantial drop in the bias between treated and control companies. T-tests confirm that none of the variables are significantly different across the two groups after matching, except for the intangible asset growth, which is weakly significantly higher in the control group after matching (p-value<10%).

Table 6a - PSM for growth analysis: sample description

	Treated	Control	Total	T/C
Total	**91,717**	**81,268**	**172,985**	**0.886**
Belgium	649	489	1,138	0.753
France	11,009	9,961	20,970	0.905
Italy	80,059	70,818	150,877	0.885
2015	2,961	2,644	5,605	0.893
2016	7,733	7,027	14,760	0.909
2017	14,666	13,173	27,839	0.898
2018	23,640	20,774	44,414	0.879
2019	13,757	12,407	26,164	0.902
2020	28,639	24,965	53,604	0.872
2021	321	278	599	0.866

Table 6b - PSM for growth analysis: diagnostics and descriptives

		Treated	Control	%bias	%delta bias	t	p>t
Ln(Total assets$_{T-1}$)	U	13.585	13.693	-7.5		-20.63	***
	M	14.147	14.077	4.8	35.4	0.51	
ΔLn(Total assets$_{T-1}$)	U	0.136	0.071	21.7		67.96	***
	M	0.115	0.092	7.8	64.1	0.74	
Ln(Sales$_{T-1}$)	U	13.820	13.914	-6.4		-17.72	***
	M	14.147	14.065	5.6	11.8	0.64	
ΔLn(Sales$_{T-1}$)	U	0.167	0.105	9.9		26.27	***
	M	-0.060	-0.034	-4.2	57.2	-0.51	
Ln(Emp. cost$_{T-1}$)	U	12.030	12.133	-6.5		-18.72	***
	M	12.396	12.330	4.1	36.2	0.47	
ΔLn(Emp. cost$_{T-1}$)	U	0.165	0.088	17.1		52.93	***
	M	-0.011	-0.028	3.8	77.9	0.35	
Ln(Int. assets$_{T-1}$)	U	7.646	7.296	7.9		23.19	***
	M	8.516	8.808	-6.5	16.8	-0.7	
ΔLn(Int. assets$_{T-1}$)	U	0.058	-0.024	4.5		14.27	***
	M	0.009	0.375	-20	-347.7	-1.94	*
Ln(Tang. assets$_{T-1}$)	U	11.026	11.072	-1.8		-5.06	***
	M	11.921	11.861	2.3	-28.2	0.28	
ΔLn(Tang. assets$_{T-1}$)	U	0.260	0.124	11.9		37.54	***
	M	0.220	0.215	0.5	96	0.05	
Productivity$_{T-1}$	U	8.350	12.392	-9.4		-21.35	***
	M	8.180	7.979	0.5	95	0.22	
Leverage $_{T-1}$	U	0.794	0.742	21.2		55.06	***
	M	0.816	0.849	-13.6	35.8	-1.23	
Cash ratio $_{T-1}$	U	0.092	0.119	-20.3		-57.64	***
	M	0.075	0.074	1.2	93.9	0.18	
Ln(Age$_{T}$)	U	2.342	2.486	-15.6		-46.74	***
	M	2.657	2.618	4.2	73	0.44	

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 grew 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 instead negative and significant meaning that over a 3-year horizon, employment growth significantly outpaced sales growth.

In terms of magnitude, 3-year logarithmic growth of total assets is 0.067 (i.e., +8.0 percentage points (p.p.), computed as exp(0.067)-1) higher in beneficiaries than matched companies. In terms of comparison, this is slightly lower than the 0.0893 Bertoni et al. (2023) found for MAP and CIP guaranteed loans in France during 2002-2016, and significantly lower than the 0.125 increase in Poland, Romania, and Spain found in the COSME report (2024) and the 0.196 increase reported in Bertoni et al. (2019) analysing MAP and CIP programs in Italy, Benelux and Nordic countries.

Over the same time window, the treatment effect on logarithmic sales growth was 0.053 (+5.4 p.p.), which again is slightly lower than the 0.0625 in Bertoni et al. (2023), and lower than the 0.103 found in the prior COSME report and the 0.1483 in Bertoni et al. (2019).

The 3-year treatment effect on growth in employment cost was 0.075 (7.8 p.p.), which is slightly higher than the 0.069 in Bertoni et al. (2023), slightly lower than the 0.088 in our latest COSME report and much lower than the 0.1693 in Bertoni et al. (2019).

Looking at fixed assets, rather than total assets, we found a very substantial increase in intangible fixed assets, which increased by 0.421 (+52.3 p.p.), and tangible fixed assets, which increased by 0.221 (+24.7 p.p.). This confirms the findings of our previous report, that the treatment effect on tangible and intangible fixed assets outpaced that on total assets and, as a consequence, that on current assets. The loan provides liquidity which beneficiary firms progressively turn into fixed assets (either tangible or intangible). This also confirms the results in Bertoni et al. (2019) that guaranteed loans lead to a faster increase in intangible assets than tangible assets.[9]

An important difference with the results of the study "Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania" is that in this sample we observed a statistically significant decline in labour productivity. This is because in this sample we observed a slower sales growth and a faster employment growth, both of which drove down

[9] However, one should consider that intangible assets typically account or a very low share of SMEs' total assets. Hence, the absolute value of the increase in the total amount of intangible assets triggered by receiving a guaranteed loan is quite small.

labour productivity. As a back-of-the-envelope calculation, pre-treatment labour productivity was 8.18 for treated companies (i.e., see Table 6b: on average, sample companies had sales of 8.18 times labour costs). Our estimates indicated that, compared to matched companies, treated companies had 3-year sales growth which is higher by 5.4 p.p. and 3-year employment growth which is higher by 7.8 p.p.. This translates into a difference in productivity by $8.18\left(\frac{1.054}{1.078}-1\right)=-0.182$, which has the same order of magnitude as the coefficient estimate in Table 7 (-0.234). It is essential to point out that this coefficient estimate is not a logarithmic difference, because productivity is a ratio. Due to the differential growth between sales and employment, three years after treatment, treated companies have sales per Euro of labour cost which are about 23.4 cents lower than control group companies. This corresponds to an approximate percentage change in productivity of -0.234/8.18 = -2.86%.

Table 7 - Baseline diff-in-diff regression results

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.067***	0.053***	0.075***	0.421***	0.221***	-0.234***
	(0.002)	(0.003)	(0.003)	(0.016)	(0.007)	(0.018)
Y_{t-1}	-0.037***	-0.026***	-0.069***	-0.228***	-0.205***	-0.143***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.060***	0.074***	-0.044***	0.025***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.070***	-0.060***	0.176***	0.036***	0.138***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.013)
Constant	0.869***	0.627***	1.100***	0.119	2.629***	2.333***
	(0.026)	(0.052)	(0.040)	(0.154)	(0.079)	(0.700)
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	**172,985**	**172,004**	**172,985**	**172,985**	**172,985**	**170,420**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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.

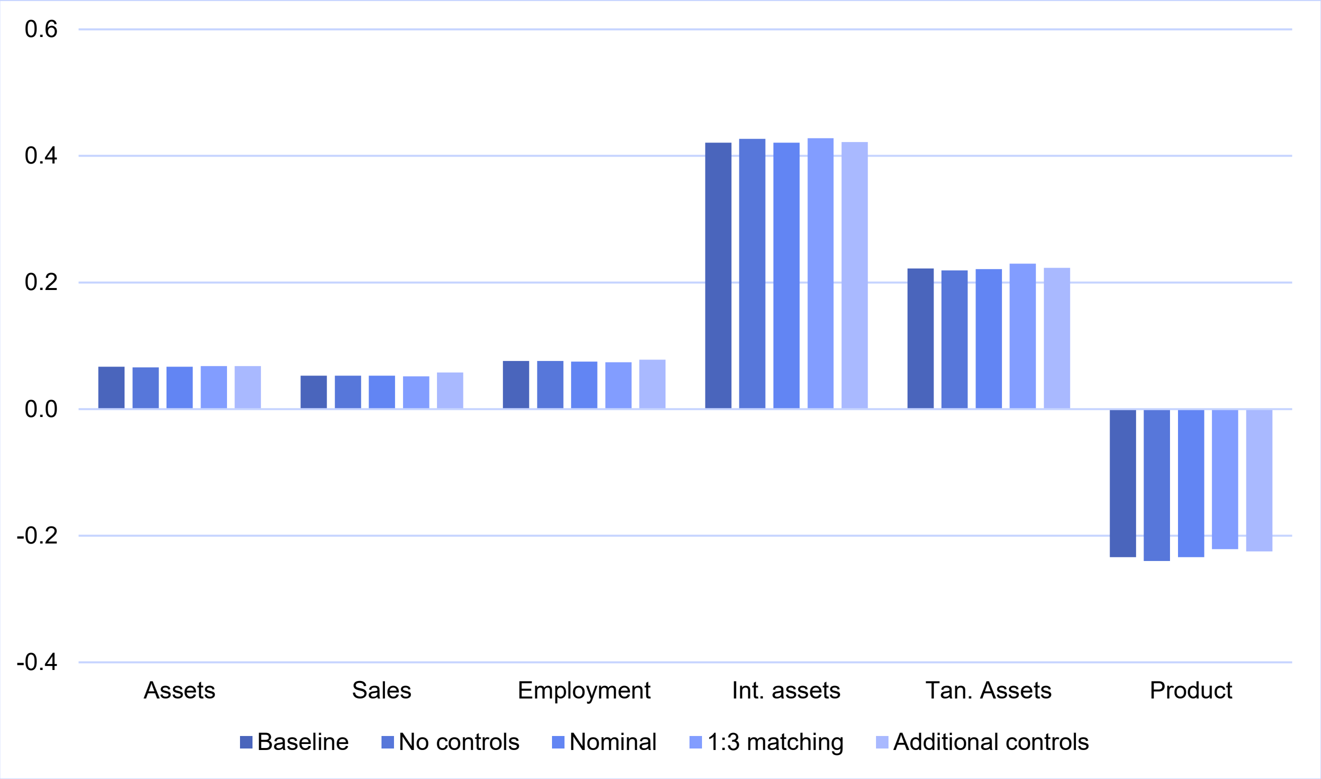
The results in Table 7 are fairly robust to alternative choices for the control group and control variables. For the sake of brevity, we report all the tables of the robustness tests in the Appendix and only show, in Figure 3, the treatment effects estimated using different methods. We replicate the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

- Changing the matching parameters (with 1:3 PSM rather than 1:1, see Table A2);
- Recalculating the dependent variable using nominal instead of inflation-adjusted amounts (see Table A3);
- Modifying the specification excluding controls and using a more complete set of controls (see Tables A4 and A5);
- Varying the time horizon (we look at 2 and 4-year growth, see Tables A6 and A7).

Including an Inverse Mills Ratio (IMR, Heckman 1979) to control for selection in the sample (see Table A8).

Overall results were very robust for all the treatment effects that were statistically significant in Table 7 (total assets, sales, employment cost, intangible fixed assets, and tangible fixed assets).

Figure 3 - Treatment effect estimates with different specifications



4.1.2 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);
- Intangible ratio (intangible/total assets =0%, between 0% and 1%, between 1% and 5%, more than 5%);
- Industry (by macro-industries);
- Country;
- Transaction year.

We report the results in Table A9 in the Appendix, however, to make the results more readable, we calculated the treatment effect for each category as a linear combination of the parameters, keeping all moderators at means except for the focal one. In other words, when comparing treatment effects over different asset classes, we considered a firm that 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 illustrated the results in Figure 4.

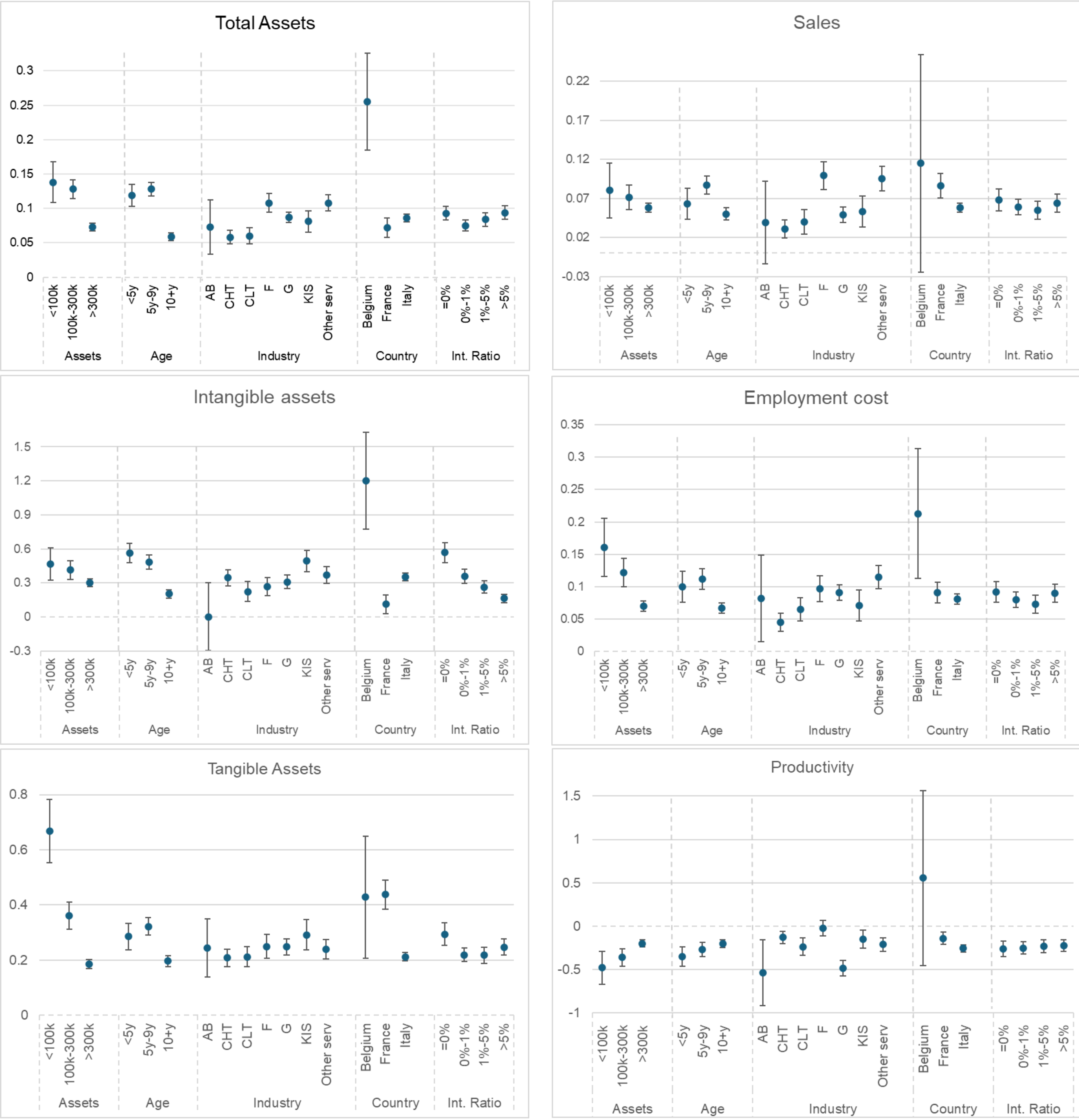
Companies of different sizes benefited from guaranteed loans in a different way. The treatment effects on total assets growth and employment growth decreased with size. In contrast, the treatment effect on sales growth did not vary significantly with size. Therefore, larger SMEs saw relatively lower losses in labour productivity (measured as sales to employment cost) from guaranteed loans than smaller SMEs. We also observed a difference in the composition of fixed assets growth: tangible fixed assets grew faster in smaller SMEs.

The results were more straightforward when it comes to age: guaranteed loans were generally associated with larger treatment effects on growth in the youngest companies.

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

Along most dimensions, treatment effects seemed to be larger in the Belgian sample than for SMEs in the other two countries. However, the small sample size led to much larger confidence intervals for the estimated effects.

Figure 2 – 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 propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. The treatment effect is interacted with categorical variables capturing size (total assets in 2015 Euros), age (in years at time of transaction), 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 reported 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$_t$	0.025***	0.004***	0.015***	0.147***	0.086***	-0.001
	(0.001)	(0.001)	(0.001)	(0.008)	(0.003)	(0.006)
Y_{t-1}	-0.268***	-0.208***	-0.339***	-0.442***	-0.382***	-0.251***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
ΔY_{t-1}	0.016***	0.021***	0.070***	0.095***	0.049***	-0.003*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Age	0.016***	-0.091***	0.077***	-0.379***	0.000	-0.174***
	(0.003)	(0.004)	(0.004)	(0.017)	(0.008)	(0.016)
Constant	3.657***	3.134***	3.945***	4.293***	4.270***	2.391***
	(0.023)	(0.028)	(0.025)	(0.041)	(0.026)	(0.040)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**1,103,987**	**1,089,767**	**1,059,434**	**1,103,406**	**1,103,617**	**1,052,873**

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 propensity-score matching. *Gloan* is an indicator variable equal to one for beneficiaries from the transaction year. Y_{t-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.

The unit of analysis was the company in a given year. The dependent variables of these models were logarithmic annual growth of assets, sales, employment cost, intangible fixed assets, tangible fixed assets and absolute annual changes in labour productivity. The key variable of interest was a step variable that switches from 0 to 1 starting from the first transaction year, and is always 0 for the untreated companies. The controls included 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 confirmed those from the previous section: beneficiaries had a faster growth rate than matched companies in assets, sales, employment, intangible and tangible fixed assets. The order of magnitude of the treatment effect was comparable to what found in the previous section (which referred to total growth over the three years starting at the beginning of the transaction year). The average treatment effect of labour productivity growth was not significantly different from zero. Our robustness checks included the use of the alternative 1:3 matching strategy (see Table A10 in the Appendix) and the inclusion of different sets of controls (Table A11 in the Appendix).

We can augment the fixed-effect specification to include time-varying treatment effect estimation. We “decomposed” the step dummy into five different dummies that identified the treatment effect in the transaction 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

	$\Delta Assets_t$	$\Delta Sales_t$	$\Delta Employment_t$	$\Delta Int.\ assets_t$	$\Delta Tan.\ assets_t$	$\Delta Productivity_t$
$Gloan_T$	0.053***	0.001	0.014***	0.167***	0.128***	-0.015**
	(0.001)	(0.001)	(0.002)	(0.009)	(0.004)	(0.008)
$Gloan_{T+1}$	0.014***	0.014***	0.024***	0.137***	0.070***	0.009
	(0.001)	(0.001)	(0.002)	(0.009)	(0.004)	(0.008)
$Gloan_{T+2}$	0.009***	0.003	0.008***	0.119***	0.063***	0.011
	(0.001)	(0.002)	(0.002)	(0.010)	(0.004)	(0.009)
$Gloan_{T+3}$	0.006***	-0.004*	0.009***	0.158***	0.054***	0.012
	(0.002)	(0.002)	(0.002)	(0.012)	(0.005)	(0.011)
$Gloan_{T+4 \text{ or more}}$	0.002	-0.013***	0.009***	0.174***	0.050***	-0.030**
	(0.002)	(0.002)	(0.003)	(0.014)	(0.006)	(0.011)
Y_t	-0.267***	-0.208***	-0.339***	-0.442***	-0.382***	-0.251***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
ΔY_{t-1}	0.015***	0.021***	0.070***	0.095***	0.049***	-0.003*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Age	0.017***	-0.091***	0.077***	-0.376***	0.004	-0.177***
	(0.003)	(0.004)	(0.004)	(0.017)	(0.008)	(0.016)
Constant	3.645***	3.136***	3.944***	4.285***	4.260***	2.398***
	(0.023)	(0.028)	(0.025)	(0.041)	(0.027)	(0.040)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**1,103,987**	**1,089,767**	**1,059,434**	**1,103,406**	**1,103,617**	**1,052,873**

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 propensity-score matching. Gloan$T$ is an indicator variable equal to one for beneficiaries in the transaction year. Gloan$T+1$- Gloan$T+3$ are indicator variables equal to one for beneficiaries 1-3 years after the transaction year. Gloant+4 and more is an indicator variable equal to one for beneficiaries 4 or more years after the transaction 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 was largest in the transaction year, but we saw a significantly higher growth rate in total assets also in the three years following the transaction year, and no evidence of mean reversion (i.e., no evidence of lower-than-average growth in following years).

For sales, the treatment effect was largest in the year after the treatment, while we saw some mean reversion starting from three years after treatment. The treatment effect on employment also peaked in year 1, but then remained positive and stable in the following years. A similar pattern was identified in tangible assets, while for intangible assets, the treatment effect was large and quite stable across all years.

Finally, we observed a significant decline in labour productivity in the transaction year because of the time lag between the growth in production inputs and production output. In the following years, the treatment was positive but not significant. We still found a negative and significant effect for longer time periods.

4.2 Credit uptake analysis

The previous analysis found that guaranteed loan beneficiaries grew more than companies that, at the time of the treatment, were similar in terms of size, growth, industry, and country. What this analysis cannot show, however, is whether beneficiaries of guaranteed loans experienced different growth from similar companies that borrowed with regular loans rather than COSME-guaranteed loans. In principle, guaranteed loans should be received by companies that wouldn't otherwise be likely to receive a loan from an intermediary, which means that beneficiaries should be more financially constrained and, hence, benefit more from the loan.

We identified "credit uptakes" experienced by treated and control group companies to shed light on this issue. These credit uptakes were defined based on a leverage measure built as the ratio between loans and total assets: $Leverage_t = \frac{Loans_t}{Total\ assets_t}$, which is bound between 0 and 1.

We identified a credit uptake when the following two conditions were met:

1. $Loans_t > Loans_{t-1}$
2. $Leverage_t - Leverage_{t-1} > 0.05$

In other words, a credit uptake is a substantial (>5 percentage points) increase in the leverage ratio on a yearly basis, which is associated with an absolute increase in loans (e.g., a company would not qualify as a "credit uptake" in a year in which total assets shrunk by 5% more than loans). The 5% threshold was coherent with previous studies (e.g., Vanacker & Manigart, 2010).

Credit uptakes, identified as substantial increases in leverage were pretty rare in our sample. Specifically, if we look at the cross-sectional baseline analysis in Section 4.1.1, credit uptakes were:

- 13.84% of the observations in our treated sample;
- 8.77% of the observations in our control group sample.

As guaranteed loans tended to be relatively small in magnitude, only about 1 in 8 beneficiaries are associated with a credit uptake. Second, control group companies have a substantially lower probability of experiencing a credit uptake in a year in which they are matched to a treated firm. In order to shed light on the importance of credit uptakes, we introduced a credit uptake dummy (*CrUp*) in our baseline model and interacted it with the *Gloan* dummy. The results are in Table 10.

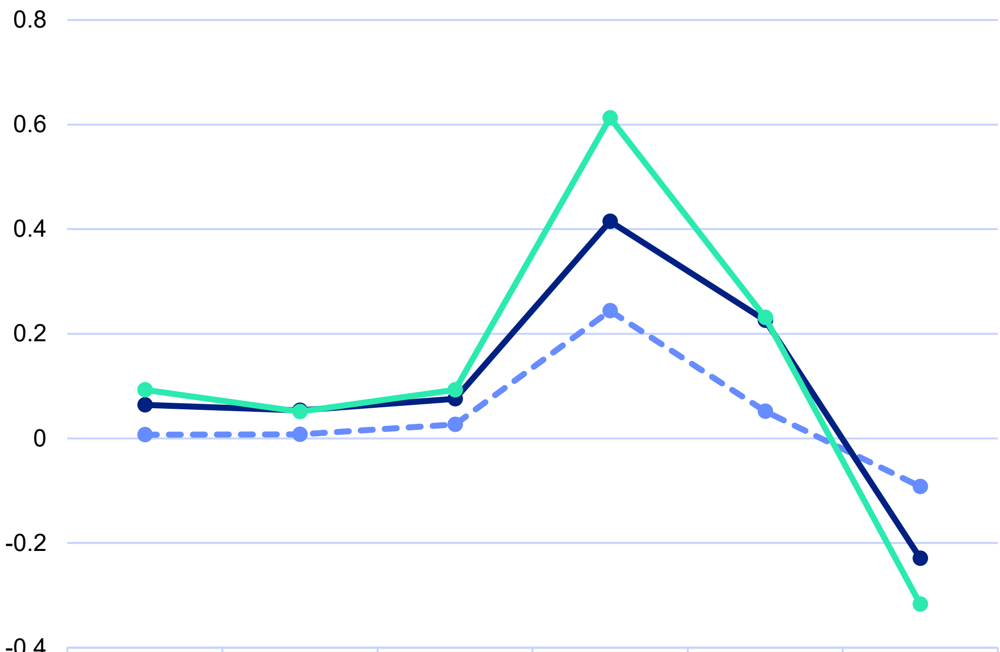
Table 10 - Treatment effect estimation with moderation of credit uptake dummy

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. Assets	Δ_3Productivity
Gloan	0.063***	0.054***	0.076***	0.415***	0.225***	-0.230***
	(0.002)	(0.003)	(0.004)	(0.017)	(0.008)	(0.019)
CrUp	0.006	0.007	0.027***	0.244***	0.052***	-0.092*
	(0.006)	(0.009)	(0.010)	(0.043)	(0.020)	(0.048)
Gloan × CrUp	0.023***	-0.010	-0.010	-0.046	-0.047*	0.004
	(0.008)	(0.010)	(0.012)	(0.052)	(0.024)	(0.060)
Y_{t-1}	-0.038***	-0.026***	-0.069***	-0.227***	-0.205***	-0.143***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.059***	0.073***	-0.045***	0.025***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.071***	-0.060***	0.178***	0.036***	0.137***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.013)
Constant	0.766***	0.530***	0.998***	-0.030	2.535***	2.351***
	(0.027)	(0.052)	(0.041)	(0.154)	(0.079)	(0.701)
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	**172,983**	**172,002**	**172,983**	**172,983**	**172,983**	**170,418**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. *CrUp* is a dummy variable that identifies credit uptakes, defined as an increase by 5% or more in leverage (loans/total assets) from t-1 to t, in a year in which loans increase in absolute amount. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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.

First, we observed from this analysis that the Gloan coefficients had a similar magnitude as the coefficients in the baseline model. This means that the treatment effect was not exclusively driven by firms that experienced credit uptakes: firms that received a guaranteed loan that did not qualify as a credit uptake grew significantly more than matched firms that did not experience credit uptakes. Put differently, even relatively small, guaranteed loans had a significant positive effect on their beneficiaries. Second, the CrUp coefficient was positive (except for Productivity) and in some specifications significant, meaning that firms that experienced a credit uptake generally did, at least for some aspects (employment, intangible assets, and tangible assets), grow faster than firms that did not. Finally, the combined effect of receiving a guaranteed loan and a credit uptake in the same year had a positive and significant effect on growth in total assets and an effect that is negative but insignificant on other growth measures. To better appreciate the meaning and magnitude of these results, we calculated the marginal effects for the three possible combinations of the two dummies (Gloan and CrUptake) against the omitted category of a company that did not receive a guaranteed loan and did not experience a credit uptake, as illustrated in Figure 5.

Figure 5 - Differential growth of guaranteed loan beneficiaries and firms that experience credit uptakes against companies that have neither



	Total assets	Sales	Employment	Intangible fixed assets	Tangible fixed assets	Productivity
CrUp=1, Gloan=0	0.007	0.008	0.027	0.244	0.052	-0.092
CrUp=0, Gloan=1	0.064	0.054	0.076	0.415	0.226	-0.229
CrUp=1, Gloan=1	0.093	0.051	0.093	0.613	0.231	-0.317

As we anticipated, credit uptakes were associated with stronger growth (except for productivity), but not to an extent that could fully explain the observed results for guaranteed loans. Beneficiaries of guaranteed loans grew more than similar companies even when we controlled for the presence of credit uptakes.

We extended this analysis along several dimensions and obtained consistent results. First, we replicated the baseline analysis by only looking at firms (treated and controls) that experience a credit uptake (Table A.12). Second, we defined leverage with a broader measure, by looking at all liabilities ($\frac{Total\ assets - Shareholder\ funds}{Total\ assets}$) (Table A.13).

Third, instead of using a dummy measure for credit uptakes we directly controlled for the increase in leverage (ΔLeverage) in our estimates. We reported results in Table 11.

Table 11 - Treatment effect estimation with moderation of increase in leverage

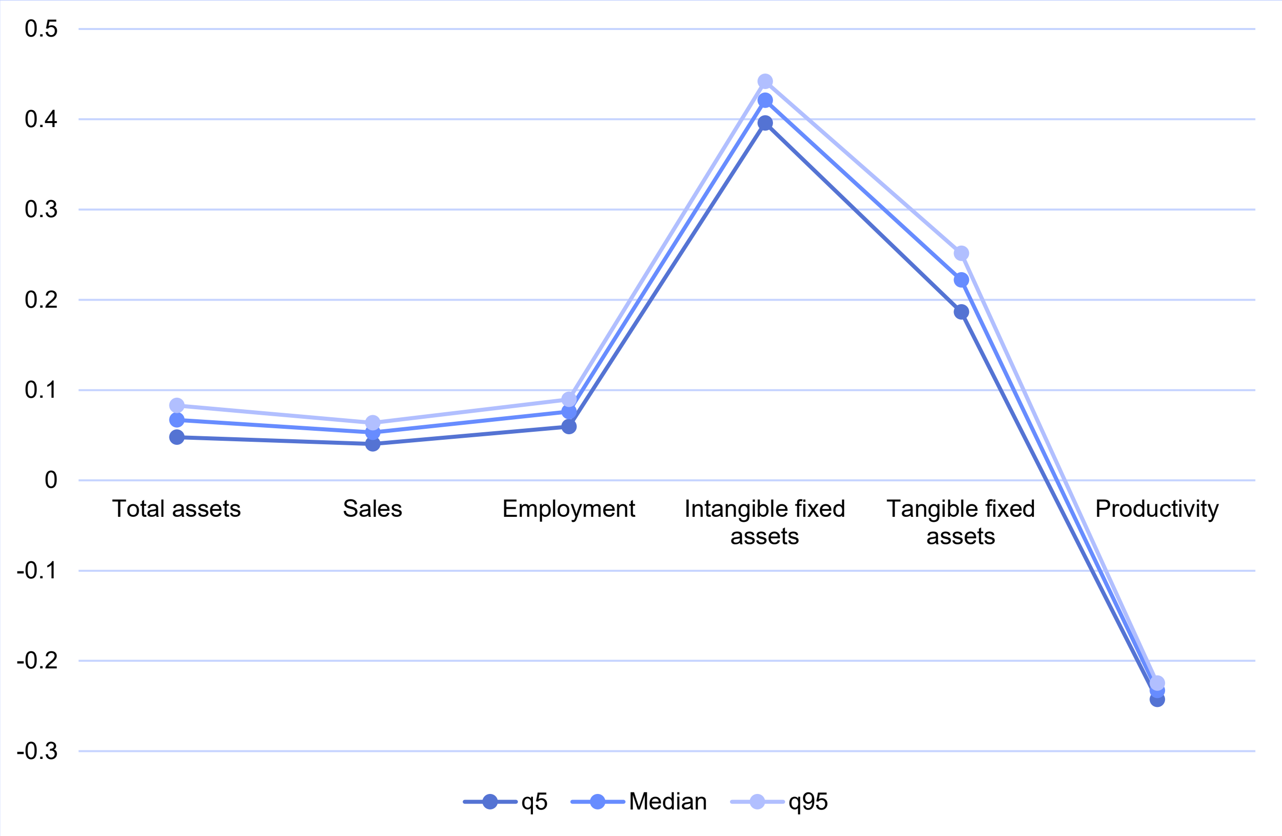
	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.067***	0.053***	0.076***	0.421***	0.222***	-0.233***
	(0.002)	(0.003)	(0.003)	(0.016)	(0.007)	(0.018)
ΔLeverage	-0.071**	-0.135***	-0.116	-0.147	-0.222**	-0.374
	(0.029)	(0.046)	(0.075)	(0.196)	(0.095)	(0.236)
Gloan × ΔLeverage	0.139***	0.092*	0.119	0.182	0.257**	0.071
	(0.033)	(0.050)	(0.079)	(0.226)	(0.107)	(0.274)
Y_{t-1}	-0.038***	-0.026***	-0.069***	-0.227***	-0.205***	-0.143***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.059***	0.073***	-0.044***	0.025***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.071***	-0.060***	0.176***	0.036***	0.136***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.013)
Constant	0.769***	0.534***	1.003***	0.021	2.542***	2.346***
	(0.027)	(0.052)	(0.041)	(0.154)	(0.079)	(0.700)
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	**172,983**	**172,002**	**172,983**	**172,983**	**172,983**	**170,418**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. *ΔLeverage* is measures the increase in the ratio between loans and total assets from t-1 to t and is centered on 0 for readability. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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.

Again, we observed that the results of the baseline model are confirmed. The *Gloan* coefficient, which measured the differential growth of treated companies with average ΔLeverage, compared to control group companies with average ΔLeverage, was similar to that in the baseline model. Whereas increases in leverage were generally associated with lower (although in some cases not significant) growth, increases in leverage for guaranteed loan beneficiaries were associated with higher growth (and, again, not always significant) than those for other companies.

We visually inspect these results in Figure 6, which compare the estimated differential growth of a treated company to a matched control group company with the same *ΔLeverage* equal to the 5th percentile, median, and 95th percentile of the variable.

Figure 6 - Treatment effect estimation for different levels of *ΔLeverage* (5th percentile, median, 95th percentile)



Overall, the key takeaway from Figure 6 is that whereas the change in leverage did appear to have a positive moderation effect on the treatment effect (i.e., larger increases in leverage in a year in which a company receives a guaranteed loan were associated with larger growth rates), the effect was economically not huge, and the beneficial effect of guaranteed loans was present even when associated to small increases in leverage.

4.3 Survival

Starting from the 111,659 loans for which we had full accounting information in T-1 and T-2 (column IV of Table 2) and its control group selected with a 1:5 PSM described in Section 3.3.2, we analysed the impact of guaranteed loans on the survival of beneficiaries in a counterfactual analysis. It is worth remembering that we did not require the availability of accounting information after treatment in this sample because this would systematically exclude failed companies (which do not register their accounting data anymore), which were instead the focus of our analysis.

An important consideration is that the unit of analysis in this case is the company and not the loan-year observation. The sample, therefore, includes 82,203 companies that received 111,659 loans and 321,065 companies that were matched with them 431,706 times. We are interested in understanding if beneficiaries' chances of dissolving were higher or lower after the treatment.

Despite the PSM, failure rates till 2024 were much higher in the control group, and as high as 19.04%, with respect to 12.19% in the treated companies.

4.3.1 Main effects

Table 12 reports the results of probit models in which the dependent variable was equal to 1 for companies that went bankrupt between the matching year and the end of 2024. The baseline model is presented in Column I and showed a negative coefficient for GLoan, indicating lower failure rates for treated companies. Marginal effects suggest that treated companies had a failure rate that is 6.8 percentage points lower than matched companies.

The size of the effect was comparable to the one found for French CIP/MAP beneficiaries in Bertoni et al. (2023), equal to 6.25 p.p., but larger than the ones in Bertoni et al. (2019, i.e., 3.35 p.p.) and in our latest COSME study (2.8 p.p.).

Results were robust when we considered alternative matching algorithms (1:3 and a 1:1 PSM instead of a 1:5 PSM, in columns II and III, respectively) when we did not add control variables (column IV), and when we did not correct for inflation (column V). We used a slightly different dependent variable in Column VI, defined as a dummy equal to 1 if the company failed within T+2, adopting the same observation horizon as for the main growth outcomes. We found similar results, and the estimated reduction in failure rates for COSME beneficiaries was equal to 4.7 p.p. in this model. As a last robustness check, we also used a Cox (1972) survival model, whose dependent variable was the hazard rate of failure in a given year conditional on having survived until that year. The Cox model accommodated data censoring in 2024, the end of the observation period. In Column VII, we found that the receipt of the loan considerably reduced the risk of being dissolved.

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

Table 12 - Failure analysis

	I	II	III	IV	V	VI	VII
	Baseline (1:5 matching)	**1:3 matching**	**1:1 matching**	**No controls**	**No correction for inflation**	**Survival till T+2**	**Cox**
Gloan	-0.293***	-0.293***	-0.289***	-0.321***	-0.293***	-0.588***	-0.632***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.012)	(0.013)
Ln(Total assets$_{T-1}$)	-0.051***	-0.051***	-0.050***		-0.051***	-0.026***	-0.099***
	(0.003)	(0.003)	(0.003)		(0.003)	(0.004)	(0.003)
ΔLn(Total assets$_{T-1}$)	-0.022	-0.032***	-0.017		-0.021	-0.170***	-0.141***
	(0.013)	(0.011)	(0.014)		(0.013)	(0.015)	(0.013)
Leverage $_{T-1}$	0.506***	0.511***	0.487***		0.506***	0.481***	0.518***
	(0.012)	(0.016)	(0.015)		(0.012)	(0.016)	(0.008)
Cash ratio $_{T-1}$	-0.535***	-0.512***	-0.509***		-0.535***	-0.300***	-0.948***
	(0.026)	(0.027)	(0.034)		(0.026)	(0.036)	(0.036)
Age	-0.113***	-0.113***	-0.114***		-0.113***	-0.072***	-0.190***
	(0.004)	(0.005)	(0.006)		(0.004)	(0.006)	(0.006)
Constant	-0.788***	-0.804***	-0.754***	-0.818***	-0.795***	-2.632***	
	(0.066)	(0.073)	(0.100)	(0.003)	(0.066)	(0.121)	
Industry FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
N	**403,257**	**290,411**	**157,794**	**403,268**	**403,257**	**403,247**	**384,526**
chi2	16,513***	14,134***	8,961***	2,421***	16,509***	7,132	21,469
Ll	-67,985	-67,930	-67,879	-72,680	-67,987	-25,276	-723,956

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 propensity-score matching. Robust standard errors in round brackets.

4.3.2 Moderators

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

Table 13 reports the average marginal effects of GLoan on the probability of failing for the different levels of the moderators. We found larger reductions in the failure rates for treated companies in the middle asset class (EUR 100k-300k), companies in the 5-9-year-old bracket, outside agriculture and mining, without intangibles, and in less recent transaction years. We run a separate analysis for country moderators, finding a stronger effect in France with respect to Italy, while the effect cannot be estimated in Belgium due to the small sample size.

Table 13 – Moderators of treatment effect on failure-rate

	Average Marginal Effect	Std.Dev.
Total assets class (EUR)		
<100k	-0.066	0.006***
100k-300k	-0.063	0.003***
≥300k	-0.067	0.002***
Age Class		
<5 years	-0.072	0.004***
5-9 years	-0.074	0.003***
≥10 years	-0.060	0.002***
Industry		
AB	-0.022	0.012*
CHT	-0.062	0.004***
CLT	-0.073	0.005***
F	-0.076	0.003***
G	-0.063	0.003***
KIservices	-0.066	0.004***
Other services	-0.064	0.003***
Intangible ratio class		
Int ratio = 0%	-0.078	0.003***
0%<Int ratio<1%	-0.057	0.003***
1%<Int ratio<5%	-0.057	0.003***
Int ratio >5%	-0.071	0.003***

	Average Marginal Effect	Std.Dev.
Table 13 continued		
Transaction year		
2015	-0.125	0.007***
2016	-0.075	0.005***
2017	-0.073	0.004***
2018	-0.068	0.003***
2019	-0.053	0.004***
2020	-0.049	0.003***
2021	-0.007	0.012
Country		
Belgium	NA	
France	-0.073	0.003***
Italy	-0.063	0.002***

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 three European countries (Belgium, France, and Italy) during 2015-2023.

We built on the existing literature that has studied the treatment effect of guaranteed loans on the growth and survival of beneficiaries and used well-established diff-in-diff models based on propensity-score matching to select an appropriate counterfactual. This approach replicated the analysis made on four European countries in the Working Paper: Economic impact assessment of the COSME Loan Guarantee Facility: evidence from Greece, Poland, Spain and Romania.

The results show that in the three years since receiving a COSME loan, guaranteed loan beneficiaries grew substantially more than matched companies in terms of assets (8.0 percentage points (p.p.)), sales (5.4 p.p.), and employment (7.8 p.p.). The positive effects on the growth of intangible fixed assets (52.3 p.p.) and tangible fixed assets (24.7 p.p.) were even more substantial. These results indicate that guaranteed loans considerably boosted beneficiaries' investments, even though one has to consider that SMEs' absolute amount of tangible and, above all, intangible fixed assets is generally low. All these estimates were statistically significant at the 1% level and stable across different choices of matching and specifications. These results are generally smaller in magnitude than those reported in the predecessor study, confirming that guaranteed loans may be more effective in boosting growth in countries where economic and financial conditions for firms are more challenging. Results on productivity show that labour productivity in this sample grew significantly less for beneficiaries than for matched firms. The economic magnitude was -0.234, corresponding to an approximately 2% decline in labour productivity. The result was consistent with the fact that we found larger benefits of COSME loans in terms of employment growth rather than sales growth, which led to a reduction in labour productivity captured by "sales per employee cost". We did not observe a similar reduction in labour productivity in our previous study, possibly pointing to differences across countries in how guaranteed loans are allocated and how beneficiary firms use them.

Treatment effects were generally larger for companies that were 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 Euro). It is worth reminding that companies younger than 2 years in the transaction year could not be included in the analysis due to missing accounting data. Based on the results of our study, one could extrapolate that the positive effects of guaranteed loans were possibly even greater for these companies, which lack a track record and are even more subject to financial constraints than other companies. Larger firms experience a less negative effect on labour productivity growth.

Results based on panel estimates confirmed the beneficial role of COSME loans on growth, showing nuanced differences in the timing of the effects. These were immediate for employment and assets growth, while they only started from year T+1 in terms of sales.

We also considered companies experiencing a credit uptake. We define a credit uptake as a yearly increase in the amount of loans that results in an increase of at least 5 percentage points in a firm's leverage ratio (loans to total assets). In other words, it captures cases where firms substantially expand their use of external credit, rather than changes driven mainly by asset contraction. Moreover, we distinguish these firms based on whether the credit uptake was associated with a guaranteed loan or not. Our findings indicate that firms that experienced a credit uptake generally grew faster than firms that did not, at least for some aspects (employment, intangible assets, and tangible assets). However, firms that received a guaranteed loan that did not qualify as a credit uptake grew significantly more than matched firms that did not experience credit uptakes. In other words, even relatively small, guaranteed loans had a significant positive effect on their beneficiaries. In addition, the combined effect of receiving a guaranteed loan and a credit uptake in the same year had a positive and significant effect on growth in total assets and an effect that was negative but insignificant on other growth measures.

In terms of survival, beneficiaries were 6.8 p.p. more likely than matched companies to survive until the end of 2024. We found a more positive effect on survival for companies with higher asset tangibility.

These results confirm what was shown in studies conducted on earlier programmes like CIP and MAP (e.g., Asdrubali and Signore, 2015; Bertoni et al. 2019; Brault and Signore, 2019), as well as results obtained in our previous COSME assessment: guaranteed-loan beneficiaries outperformed matched companies both in terms of growth and survival.

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 found that guaranteed loans were associated with a substantial additional growth of the beneficiaries. This holds in each of the three countries in our analysis, and for each of the growth variables (assets, sales, and employment) we considered. Beneficiaries also invested substantially more in tangible and, more interestingly, intangible fixed assets (even though the estimated increase in the amount of intangible assets triggered by the receipt of a guaranteed loan was limited in absolute size). 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).

Annexes

Annex 1: Bias reduction in variables of interest with different PSM

Figure A1a. Bias reduction in variables of interest after the “fully fledged” PSM

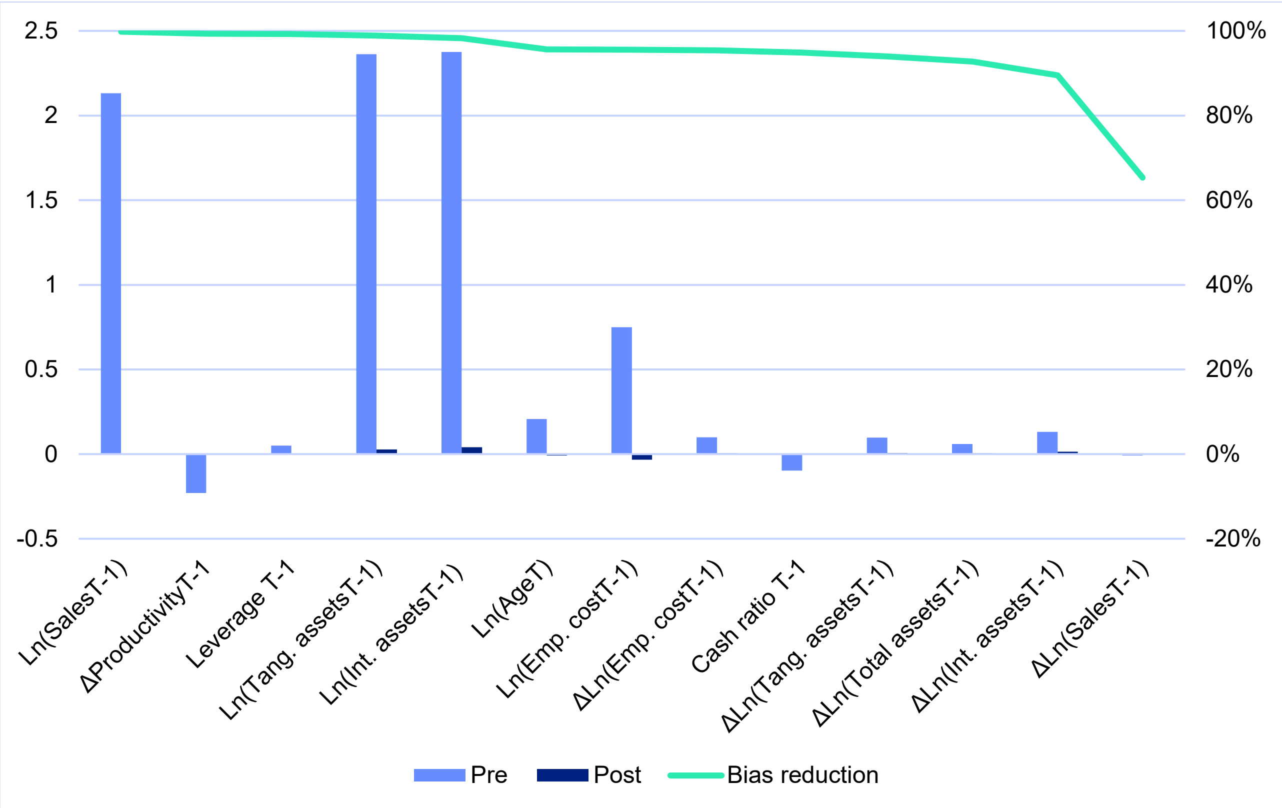
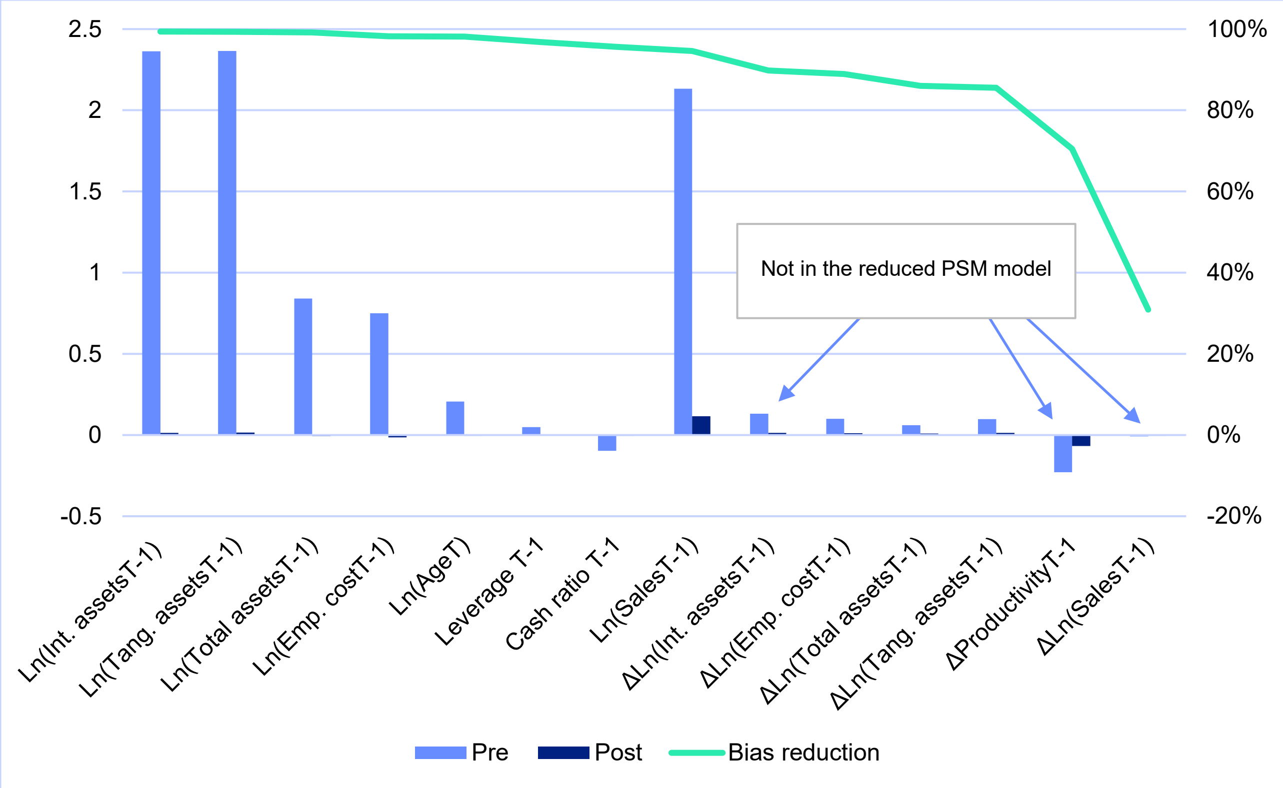


Figure A1b. Bias reduction in variables of interest after the “reduced” PSM



Annex 2: Cross sectional analysis

Table A2. 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	0.068***	0.052***	0.074***	0.428***	0.230***	-0.221***
	(0.002)	(0.002)	(0.003)	(0.013)	(0.006)	(0.015)
Y_{t-1}	-0.038***	-0.027***	-0.069***	-0.228***	-0.204***	-0.158***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)
$\Delta_1 Y_{t-1}$	0.139***	0.057***	0.072***	-0.045***	0.018***	-0.077***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Age	-0.107***	-0.071***	-0.060***	0.184***	0.033***	0.123***
	(0.001)	(0.002)	(0.002)	(0.008)	(0.004)	(0.010)
Constant	0.805***	0.572***	1.033***	-0.031	2.540***	1.988***
	(0.021)	(0.044)	(0.033)	(0.135)	(0.068)	(0.380)
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	**301,599**	**300,101**	**301,599**	**301,599**	**301,599**	**295,949**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on Δ_3Y, 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 transaction year. Each guaranteed loan beneficiary is matched to 3 non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A3. Cross-sectional diff-in-diff on nominal values

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.067***	0.053***	0.075***	0.421***	0.221***	-0.234***
	(0.002)	(0.003)	(0.003)	(0.016)	(0.007)	(0.018)
Y_{t-1}	-0.037***	-0.026***	-0.069***	-0.228***	-0.205***	-0.143***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.060***	0.074***	-0.044***	0.025***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.070***	-0.060***	0.176***	0.036***	0.138***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.013)
Constant	0.869***	0.627***	1.100***	0.119	2.629***	2.333***
	(0.026)	(0.052)	(0.040)	(0.154)	(0.079)	(0.700)
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	**172,985**	**172,004**	**172,985**	**172,985**	**172,985**	**170,420**

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). Each guaranteed loan beneficiary is matched to 1 non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year, without controlling for inflation. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level (in logs) of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A4. Cross-sectional diff-in-diff regression without controls

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.066***	0.053***	0.076***	0.427***	0.219***	-0.240***
	(0.002)	(0.003)	(0.003)	(0.017)	(0.008)	(0.019)
Constant	0.166***	0.017***	-0.002	-0.491***	0.032***	0.090***
	(0.002)	(0.002)	(0.003)	(0.012)	(0.006)	(0.013)
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	**172,985**	**172,010**	**172,985**	**172,985**	**172,985**	**172,010**

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 propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Robust standard errors in round brackets.

Table A5. Cross-sectional diff-in-diff regression with all controls

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.068***	0.058***	0.078***	0.422***	0.223***	-0.225***
	(0.002)	(0.003)	(0.003)	(0.016)	(0.007)	(0.017)
ΔLn(Total assets$_{T-1}$)	0.065***	0.186***	0.207***	0.288***	0.271***	-0.088*
	(0.007)	(0.009)	(0.010)	(0.038)	(0.022)	(0.046)
ΔLn(Sales$_{T-1}$)	0.037***	-0.023**	0.044***	0.028	0.058***	-0.114**
	(0.007)	(0.010)	(0.010)	(0.033)	(0.020)	(0.049)
ΔLn(Emp. cost$_{T-1}$)	0.063***	0.044***	0.025**	0.091***	0.154***	-0.253***
	(0.006)	(0.009)	(0.011)	(0.035)	(0.019)	(0.058)
ΔLn(Int. assets$_{T-1}$)	0.003***	0.004***	0.002**	-0.032***	0.010***	0.005
	(0.001)	(0.001)	(0.001)	(0.005)	(0.002)	(0.005)
ΔLn(Tang. assets$_{T-1}$)	0.011***	0.008***	0.009***	-0.005	-0.010**	-0.019*
	(0.002)	(0.002)	(0.002)	(0.009)	(0.005)	(0.011)
ΔProductivity$_{T-1}$	0.001	-0.004***	0.005***	0.003	0.008***	-0.099***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.003)	(0.009)
Ln(Total assets$_{T-1}$)	-0.171***	0.026***	-0.016***	0.205***	0.198***	0.174***
	(0.003)	(0.006)	(0.004)	(0.016)	(0.010)	(0.020)
Ln(Sales$_{T-1}$)	0.141***	-0.066***	0.185***	0.190***	0.105***	-0.910***
	(0.005)	(0.011)	(0.007)	(0.032)	(0.019)	(0.233)
Ln(Emp. cost$_{T-1}$)	0.004	0.011	-0.207***	0.085***	0.007	0.845***
	(0.003)	(0.007)	(0.006)	(0.028)	(0.017)	(0.227)
Ln(Int. assets$_{T-1}$)	-0.000	0.001***	0.004***	-0.281***	0.004***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.003)
Ln(Tang. assets$_{T-1}$)	0.007***	0.012***	0.017***	0.022***	-0.295***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.007)
Productivity$_{T-1}$	0.000	0.002**	0.001*	-0.007**	-0.002	-0.078***
	(0.000)	(0.001)	(0.001)	(0.003)	(0.002)	(0.027)
Leverage$_{T-1}$	0.136***	0.109***	0.170***	-0.219***	0.359***	-0.513***
	(0.012)	(0.016)	(0.016)	(0.077)	(0.042)	(0.080)
Cash ratio$_{T-1}$	-0.153***	-0.085***	-0.117***	-0.260***	-0.371***	0.129***
	(0.008)	(0.011)	(0.013)	(0.039)	(0.028)	(0.048)
Age	-0.086***	-0.058***	-0.055***	-0.068***	-0.017***	0.010
	(0.002)	(0.002)	(0.003)	(0.012)	(0.006)	(0.014)
Constant	0.544***	0.409***	-0.014	-5.950***	-0.514***	2.106***
	(0.042)	(0.051)	(0.053)	(0.309)	(0.112)	(0.655)
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	**170,453**	**170,420**	**170,453**	**170,453**	**170,453**	**170,420**

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 propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Robust standard errors in round brackets.

Table A6. Treatment effect estimation on 2-year growth

	Δ_2Assets	Δ_2Sales	Δ_2Employment	Δ_2Int. assets	Δ_2Tan. assets	Δ_2Productivity
Gloan	0.059***	0.035***	0.049***	0.336***	0.178***	-0.170***
	(0.002)	(0.002)	(0.003)	(0.013)	(0.006)	(0.015)
Y_{t-1}	-0.034***	-0.026***	-0.057***	-0.167***	-0.173***	-0.113***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.014)
$\Delta_1 Y_{t-1}$	0.103***	0.044***	0.070***	-0.029***	0.025***	-0.066***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Age	-0.084***	-0.060***	-0.052***	0.089***	0.016***	0.105***
	(0.001)	(0.002)	(0.002)	(0.008)	(0.004)	(0.011)
Constant	0.756***	0.537***	0.926***	0.226*	2.279***	1.814***
	(0.022)	(0.050)	(0.032)	(0.133)	(0.071)	(0.565)
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	**171,364**	**169,779**	**170,248**	**171,359**	**171,361**	**167,762**

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 transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level (in logs) of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A7. Treatment effect estimation on 4-year growth

	Δ_4Assets	Δ_4Sales	Δ_4Employment	Δ_4Int. assets	Δ_4Tan. assets	Δ_4Productivity
Gloan	0.067***	0.063***	0.067***	0.488***	0.243***	-0.251***
	(0.003)	(0.004)	(0.005)	(0.021)	(0.010)	(0.024)
Y_{t-1}	-0.043***	-0.030***	-0.080***	-0.274***	-0.238***	-0.200***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
$\Delta_1 Y_{t-1}$	0.174***	0.068***	0.078***	-0.117***	0.009	-0.064***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Age	-0.128***	-0.075***	-0.077***	0.197***	0.062***	0.163***
	(0.002)	(0.003)	(0.003)	(0.013)	(0.007)	(0.015)
Constant	1.122***	0.827***	1.378***	0.460**	3.260***	2.092***
	(0.039)	(0.081)	(0.056)	(0.222)	(0.106)	(0.414)
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	**115,822**	**113,951**	**112,835**	**115,809**	**115,810**	**111,173**

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 propensity-score matching. The dependent variables are logarithmic differences between three years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level (in logs) of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A8. 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	0.067***	0.052***	0.073***	0.413***	0.218***	-0.234***
	(0.002)	(0.003)	(0.003)	(0.016)	(0.007)	(0.018)
Y_{t-1}	-0.035***	-0.061***	-0.140***	-0.272***	-0.289***	-0.143***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.063***	0.082***	-0.026***	0.034***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.074***	-0.077***	-0.025**	-0.023***	0.126***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.018)
IMR	0.077	-1.402***	-3.659***	-13.437***	-8.824***	-0.742*
	(0.103)	(0.122)	(0.083)	(0.237)	(0.181)	(0.450)
Constant	0.769***	2.390***	5.281***	12.955***	11.822***	3.018***
	(0.137)	(0.175)	(0.112)	(0.274)	(0.221)	(0.476)
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	**172,985**	**172,004**	**172,985**	**172,985**	**172,985**	**170,420**

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 propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level (in logs) of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A9 - Treatment effect moderators

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.335***	0.120	0.314***	1.489***	0.955***	-0.109
	(0.043)	(0.078)	(0.070)	(0.273)	(0.138)	(0.564)
(Gloan) × (100k<Assets≤300k)	-0.010	-0.009	-0.039	-0.055	-0.306***	0.117
	(0.016)	(0.019)	(0.025)	(0.081)	(0.063)	(0.105)
Gloan × (Assets >300k)	-0.064***	-0.022	-0.091***	-0.167**	-0.483***	0.280***
	(0.015)	(0.019)	(0.024)	(0.077)	(0.059)	(0.100)
Gloan × (5y<Age<10y)	0.009	0.024**	0.012	-0.080	0.037	0.083
	(0.009)	(0.012)	(0.014)	(0.053)	(0.030)	(0.070)
Gloan × (Age≥10y)	-0.060***	-0.013	-0.033***	-0.362***	-0.089***	0.150**
	(0.008)	(0.011)	(0.013)	(0.049)	(0.028)	(0.063)
Gloan × (Industry CHT)	-0.015	-0.008	-0.037	0.343**	-0.036	0.405**
	(0.021)	(0.028)	(0.034)	(0.157)	(0.056)	(0.197)
Gloan × (Industry CLT)	-0.013	0.001	-0.016	0.221	-0.032	0.300
	(0.021)	(0.028)	(0.035)	(0.159)	(0.057)	(0.200)
Gloan × (Industry F)	0.035*	0.060**	0.015	0.263*	0.004	0.514***
	(0.021)	(0.028)	(0.035)	(0.158)	(0.058)	(0.199)
Gloan × (Industry G)	0.014	0.010	0.010	0.306**	0.004	0.050
	(0.021)	(0.027)	(0.034)	(0.156)	(0.056)	(0.199)
Gloan × (Industry KIS)	0.008	0.015	-0.011	0.490***	0.047	0.386*
	(0.022)	(0.029)	(0.036)	(0.160)	(0.061)	(0.201)
Gloan × (Industry Other serv.)	0.035*	0.056**	0.033	0.366**	-0.005	0.325
	(0.021)	(0.028)	(0.035)	(0.157)	(0.057)	(0.198)
Gloan × (France)	-0.183***	-0.030	-0.121**	-1.090***	0.010	-0.696
	(0.036)	(0.072)	(0.052)	(0.220)	(0.117)	(0.517)
Gloan × (Italy)	-0.169***	-0.057	-0.131**	-0.850***	-0.216*	-0.811
	(0.036)	(0.071)	(0.052)	(0.218)	(0.114)	(0.515)
Gloan × (0%<Int. ratio≤1%)	-0.018***	-0.008	-0.012	-0.206***	-0.074***	0.012
	(0.007)	(0.009)	(0.010)	(0.055)	(0.025)	(0.058)

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Table A9 continued						
Gloan × (1%<Int. ratio≤5%)	-0.009	-0.013	-0.019*	-0.303***	-0.077***	0.030
	(0.007)	(0.009)	(0.011)	(0.053)	(0.026)	(0.061)
Gloan × (Int. ratio>5%)	0.002	-0.004	-0.002	-0.405***	-0.047*	0.040
	(0.007)	(0.009)	(0.011)	(0.049)	(0.027)	(0.057)
Constant	0.256***	0.144**	0.066	-0.272	0.099	0.326
	(0.033)	(0.062)	(0.057)	(0.196)	(0.110)	(0.345)
Fixed effects						
Assets	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Int. ratio	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	**172,985**	**172,010**	**172,985**	**172,985**	**172,985**	**172,010**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. The variable is interacted with categorical variables capturing size (total assets in 2015 Euros), age (in years at time of transaction), 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%, Transaction year 2015. Robust standard errors in round brackets.

Annex 3: Fixed-effect panel data models

Table A10. Fixed-effect panel data model, 1:3 PSM

	$\Delta Assets_t$	$\Delta Sales_t$	$\Delta Employment_t$	$\Delta Int.\ assets_t$	$\Delta Tan.\ assets_t$	$\Delta Productivity_t$
$Gloan_t$	0.025***	0.007***	0.017***	0.159***	0.091***	-0.002
	(0.001)	(0.001)	(0.001)	(0.007)	(0.003)	(0.006)
Y_{t-1}	-0.265***	-0.207***	-0.340***	-0.442***	-0.379***	-0.256***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
ΔY_{t-1}	0.014***	0.018***	0.067***	0.096***	0.049***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.006**	-0.100***	0.062***	-0.477***	-0.033***	-0.167***
	(0.002)	(0.003)	(0.003)	(0.013)	(0.007)	(0.013)
Constant	3.649***	3.142***	3.988***	4.478***	4.314***	2.387***
	(0.019)	(0.023)	(0.020)	(0.033)	(0.022)	(0.032)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	**1,714,791**	**1,692,931**	**1,643,418**	**1,713,853**	**1,714,224**	**1,633,387**

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 propensity-score matching (1:3 ratio, nearest neighbour). *Gloan* is an indicator variable equal to one for beneficiaries from the transaction year. Y_{t-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 A11. Fixed-effect panel data model, all controls

	ΔAssets$_t$	ΔSales$_t$	ΔEmployment$_t$	ΔInt. assets$_t$	ΔTan. assets$_t$	ΔProductivity$_t$
Gloan$_t$	0.026***	0.007***	0.008***	0.111***	0.071***	0.009
	(0.001)	(0.001)	(0.001)	(0.008)	(0.003)	(0.006)
ΔLn(Total assets$_{T-1}$)	0.013***	0.126***	0.082***	-0.025**	0.043***	0.183***
	(0.002)	(0.003)	(0.002)	(0.010)	(0.005)	(0.011)
ΔLn(Sales$_{T-1}$)	0.004**	-0.041***	0.039***	0.056***	0.005	0.037***
	(0.002)	(0.003)	(0.003)	(0.010)	(0.005)	(0.013)
ΔLn(Emp. cost$_{T-1}$)	0.001	0.039***	0.028***	0.009	0.018***	-0.338***
	(0.001)	(0.002)	(0.003)	(0.010)	(0.005)	(0.012)
ΔLn(Int. assets$_{T-1}$)	0.002***	0.001***	0.002***	0.100***	0.002***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
ΔLn(Tang. assets$_{T-1}$)	0.004***	-0.000	0.004***	0.015***	0.057***	-0.023***
	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
ΔProductivity$_{T-1}$	-0.002***	0.002***	-0.009***	-0.003*	-0.001	-0.037***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
Ln(Total assets$_{T-1}$)	-0.364***	0.064***	0.064***	0.317***	0.181***	0.086***
	(0.002)	(0.004)	(0.003)	(0.011)	(0.006)	(0.012)
Ln(Sales$_{T-1}$)	0.061***	-0.336***	0.042***	0.041***	0.100***	-0.452***
	(0.003)	(0.007)	(0.004)	(0.012)	(0.007)	(0.020)
Ln(Emp. cost$_{T-1}$)	0.022***	-0.010***	-0.336***	0.074***	0.017***	0.010
	(0.002)	(0.004)	(0.005)	(0.010)	(0.005)	(0.014)
Ln(Int. assets$_{T-1}$)	0.001***	0.003***	0.002***	-0.465***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Ln(Tang. assets$_{T-1}$)	0.006***	0.013***	0.011***	0.016***	-0.421***	-0.003
	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Productivity$_{T-1}$	0.001***	-0.004***	0.011***	0.000	-0.000	-0.244***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Cash ratio$_{T-1}$	-0.018***	-0.042***	0.098***	-0.139***	0.206***	-0.685***
	(0.004)	(0.005)	(0.006)	(0.028)	(0.013)	(0.024)

	$\Delta Assets_t$	$\Delta Sales_t$	$\Delta Employment_t$	$\Delta Int.\ assets_t$	$\Delta Tan.\ assets_t$	$\Delta Productivity_t$
Table A11 continued						
$Leverage_{T-1}$	0.006*	0.013***	-0.002	0.152***	0.081***	0.009
	(0.003)	(0.005)	(0.005)	(0.025)	(0.010)	(0.023)
Age	0.055***	-0.022***	0.043***	-0.655***	-0.137***	-0.231***
	(0.003)	(0.004)	(0.004)	(0.020)	(0.008)	(0.018)
Constant	3.697***	3.874***	2.304***	-0.781***	0.937***	7.527***
	(0.021)	(0.035)	(0.030)	(0.112)	(0.057)	(0.124)
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 propensity-score matching (1:1 ratio, nearest neighbour). *Gloan* is an indicator variable equal to one for beneficiaries from the transaction year. All models include fixed effects by firm and year. Robust standard errors in round brackets.

Annex 4: Credit uptake analysis

Table A12. Diff-in-diff estimates, credit uptake firms only

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.084***	0.042***	0.062***	0.335***	0.170***	-0.221***
	(0.008)	(0.010)	(0.012)	(0.050)	(0.023)	(0.057)
Y_{t-1}	-0.041***	-0.030***	-0.093***	-0.257***	-0.223***	-0.178***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.011)	(0.007)
$\Delta_1 Y_{t-1}$	0.161***	0.092***	0.084***	-0.022	0.027**	-0.054***
	(0.016)	(0.016)	(0.023)	(0.014)	(0.014)	(0.018)
Age	-0.113***	-0.067***	-0.056***	0.069**	-0.010	0.148***
	(0.005)	(0.006)	(0.007)	(0.029)	(0.014)	(0.034)
Constant	0.797***	0.468***	1.270***	0.623	2.616***	2.786***
	(0.076)	(0.154)	(0.112)	(0.414)	(0.232)	(0.890)
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	**19,766**	**19,564**	**19,766**	**19,766**	**19,766**	**19,430**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. The sample includes only companies that experience a credit uptake in year *t*, defined as an increase in leverage (loans/total assets) by 5% or more, which is associated with an increase in loans. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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 A13. Treatment effect estimation with moderation of credit uptake dummy (alternative definition)

	Δ_3Assets	Δ_3Sales	Δ_3Employment	Δ_3Int. assets	Δ_3Tan. assets	Δ_3Productivity
Gloan	0.063***	0.054***	0.076***	0.415***	0.225***	-0.230***
	(0.002)	(0.003)	(0.004)	(0.017)	(0.008)	(0.019)
CrUp	0.006	0.007	0.027***	0.244***	0.052***	-0.092*
	(0.006)	(0.009)	(0.010)	(0.043)	(0.020)	(0.048)
Gloan × CrUp	0.023***	-0.010	-0.010	-0.046	-0.047*	0.004
	(0.008)	(0.010)	(0.012)	(0.052)	(0.024)	(0.060)
Y_{t-1}	-0.038***	-0.026***	-0.069***	-0.227***	-0.205***	-0.143***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.018)
$\Delta_1 Y_{t-1}$	0.142***	0.059***	0.073***	-0.045***	0.025***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Age	-0.107***	-0.071***	-0.060***	0.178***	0.036***	0.137***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.005)	(0.013)
Constant	0.766***	0.530***	0.998***	-0.030	2.535***	2.351***
	(0.027)	(0.052)	(0.041)	(0.154)	(0.079)	(0.701)
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	**172,983**	**172,002**	**172,983**	**172,983**	**172,983**	**170,418**

Legend: ***: p-value<1%, **: p-value<5%, *: p-value<10% The table reports diff-in-diff estimates on $\Delta_3 Y$, 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 transaction year. Guaranteed loan beneficiaries (the treated units) are matched to non-beneficiaries using propensity-score matching. The dependent variables are logarithmic differences between two years after and one year before the transaction year. *Gloan* is an indicator variable equal to one for beneficiaries. *CrUp* is a dummy variable that identifies credit uptakes, defined as an increase by 5% or more in leverage (l1-Shareholder's equity/total assets) from t-1 to t, in a year in which liabilities increase in absolute amount. Y_{t-1} is the pre-treatment level of the variable of interest. $\Delta_1 Y_{t-1}$ is the pre-treatment growth (from two to one year before the transaction 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.

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