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Econometric study on the impact of EU loan guarantee financial instruments on growth and jobs of SMEs

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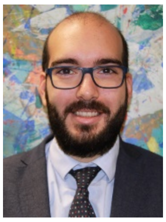

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Abstract[1]

This working paper investigates the economic effects of guaranteed loans granted under the EU programmes MAP and CIP on SMEs' growth in Italy, the Benelux and the Nordic countries (Denmark, Finland, Norway and Sweden) from 2002 to 2016. In these macro-regions, the facilities supported 174,107 loans to SMEs, for a total of EUR 15.58bn. Using a sample of these loans with corresponding firm-level data, this study estimates the average treatment effect on firms' growth, profitability, assets intangibility and survival. The analysis compares beneficiary SMEs to similar firms that were not supported by the programmes, identified through coarsened exact matching (CEM) and propensity score matching (PSM). Overall, guaranteed loans are found to positively affect the growth in assets (+19.6 percentage points over the two years after the end of the signature year), sales (+14.8 percentage points), employment (+16.9 percentage points) and the share of intangible assets (+1 percentage point). No significant effect on profits is observed. Beneficiary SMEs also have lower bankruptcy rates compared to control firms. Consistent with the literature on financing constraints, positive effects are stronger for smaller, younger SMEs. Treatment effects are more pronounced in the Benelux and Nordic countries, mostly due to the sample composition of treated firms in each macro-region.

Keywords: EIF; credit guarantees; credit constraints; real effects; small and medium-sized enterprises

JEL codes: G2, H25, O16

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Executive Summary

The aim of this Working Paper is to investigate the effects of **guaranteed loans** granted between 2002 and 2016 under the European Union's **MAP and CIP programmes** managed by the **European Investment Fund** (EIF) on the growth of small and medium sized enterprises (**SMEs**) located in Italy, the Benelux and Nordic countries (Denmark, Sweden, Finland and Norway). In particular, the paper addresses the following issues:

- Did the beneficiary SMEs (i.e., the SMEs benefitting from loan guarantees) create jobs, increase their sales and assets, become profitable and invest in intangible assets more than they would otherwise have?
- What is the evolution over time of these effects?
- Are there systematic differences in the magnitude of these effects across the three geographical areas under consideration?
- Are the effects:
    - stronger for smaller and younger firms, allegedly the most financially constrained?
    - dependent on the amount of the guaranteed loan?
    - different across industries?
- Are beneficiary SMEs more likely to survive due to their access to these schemes?

To this end, the study considers **174,107 guaranteed loans** for a total amount of EUR **15.58 billion**.

Because of data availability, the **econometric analysis** that is at the core of this study focuses on beneficiaries that have a **limited liability** legal form and for which accounting data were available. The total amount of the guaranteed loans received by these firms is approximately equal to 1/3 of the amount indicated above. Potential concerns regarding the representativeness of our results are addressed in a specific appendix, which shows that our main findings are robust to data loss.

We provide a reliable estimate of the **economic additionality** of guaranteed loans in terms of total assets, sales and employment growth. We also investigate the effect on profitability, intangible-to-total assets (as a proxy for innovation) and likelihood of survival. We employ a rigorous econometric approach to estimate the **"treatment effect"** of guaranteed loans. Our econometric models compare the evolution of these variables for beneficiaries following the receipt of the loan with the corresponding evolution for a **control group** of non-beneficiary firms. Such control group is composed by "twin" firms that, while not receiving MAP- and/or CIP-guaranteed loans, exhibited very similar characteristics to the beneficiaries before the receipt of the loan.

Finally, we present some evidence on the default rates of **sole proprietorships**, which are excluded from the main analysis due to limited data availability. Due to differences in the way default data was reported in MAP and CIP, this additional analysis could only be carried out for CIP beneficiaries.

The **main results** of the analysis can be summarised as follows:

- After receiving a guaranteed loan, beneficiaries grew more rapidly than non-beneficiaries in terms of total assets, sales and employment. The additional growth is quite large: two years after the end of the signature year, it is equal to **+19.6 percentage points for total assets, 14.8 for sales, and 16.9 for employment costs.**
- Receipt of guaranteed loans leads to an estimated **increase** equal to **1 percentage point in intangible-to-total assets** 2 years after the end of the signature year, which is approximately 1/3 of the average share of intangible-to-total assets in the sample.
- Beneficiaries were **more likely to survive** following the granting of the guaranteed loan and, again, the effect is quite large: the probability to default within 2 years after the end of the signature year is 30% smaller for beneficiaries than for twin non-beneficiaries.
- We do not detect significant effects of guaranteed loans on firm profits before taxes.
- On average, **sole proprietorships in Italy have relatively lower default rates** than limited liability companies. However, **this is the opposite in Belgium**, where sole proprietorships are instead much more likely to default than limited liability companies are.

Our results show that the magnitude of the economic additionality of guaranteed loans **varies considerably according to the characteristics of the beneficiary firms**. Guaranteed loans have stronger effects on **smaller and younger companies**. This is consistent with the tenet that these firms are the most subject to financial constraints. The effects are **larger for firms in services** than in manufacturing industries, but do not seem to be larger in high-tech and knowledge-intensive sectors vs. low-tech sectors. As expected, **larger guaranteed loans** trigger **larger positive effects** on growth.

Lastly, our study documents the **differences in the magnitude of the economic additionality** across the **three geographical areas** under consideration. The effects in Benelux are almost twice as large as in the Nordic countries, and the effects in the Nordic countries are more than double in size than those in Italy. Most of these differences can be traced to the different mix of loan sizes, as well as the size, age and industry of beneficiary firms in the macro-regions. Guaranteed loans are more beneficial when they are larger and when they are granted to smaller and younger beneficiaries.

The differences in the profiles of beneficiary firms across the three macro-regions are due both to differences in the underlying economies and to differences in the way the programme has been administered in the three macro-regions.

In conclusion, our analysis shows that **guaranteed loans were effective in boosting the growth and increasing the chances of survival of beneficiaries**. In line with the theory that more financially constrained companies are subject to stronger barriers to growth, we find that **the effectiveness of guaranteed loans is greater when the beneficiary is smaller and/or younger**. However, these results cannot be immediately taken as a recommendation to target guarantee programmes exclusively towards these companies. In this perspective, our evidence provides a necessary but not a sufficient argument, as we exclusively look at the economic benefits of guarantees, **without considerations to the implied financial risk and cost**, which are likely to be higher for younger and smaller firms. **Further research would be necessary to shed light on the tradeoff in terms of cost and benefit.**

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1 Introduction

It is well known that small and medium-sized enterprises (SMEs) suffer from the existence of a structural lending gap, i.e. some SMEs have no access to bank financing at a reasonable interest rate, which negatively influences their economic performance (Beck, Demirgüç-kunt, & Martinez, 2008; Kraemer-Eis et al., 2015). In order to alleviate these problems, since 1998, the European Union (EU) provides loan portfolio guarantees to financial intermediaries serving SMEs.

Because of their broad use worldwide, guaranteed loans received significant attention in the academic literature. However, empirical evidence on the effect of such programmes on beneficiary firms strongly depends on the specific guaranteed loans programme considered. In fact, loan guarantee programmes are often designed at the national level in a variety of ways, and the selected design is not always effective (Beck, Klapper, & Mendoza, 2010; Riding & Haines, 2001). Brown and Earle (2017) recently focused on the Small Business Administration (SBA) guaranteed loans programme, available to SMEs in the U.S. since the mid-1990s, finding a positive association between receipt of financial access to SBA loans and employment growth.

The guaranteed loans supported by the European Commission were object of two recent evaluation studies. Asdrubali and Signore (2015) evaluated the impact of the *Multi-Annual Programme for enterprise and entrepreneurship* (MAP), and in particular for SMEs. In this programme, guaranteed loans were awarded to SMEs located in Central, Eastern and South-Eastern European (CESEE) countries in the period 2005-2012. Bertoni, Colombo and Quas (2018a) focussed on guaranteed loans awarded under both the MAP and its successor CIP (Competitiveness and Innovation Framework Programme) in the period 2002-2016 and their impact on SMEs located in France.

The literature reveals that the impact of guaranteed loans depends on the context in which beneficiaries operate (Briozzo & Cardone-Riportella, 2016; Brown & Earle, 2017). Therefore, this paper also aims at shedding further light on the conditions under which SMEs benefit the most from these schemes, with particular reference to firm-level, industry-level and loan-level characteristics. Moreover, the unique multi-country approach used in this analysis allows us to detail how country specificities influence the effects of receipt of guaranteed loans on firm performance.

In this working paper we focus on the population of SMEs located in three geographical areas within the EU – Italy, Benelux and Nordic countries (Denmark, Sweden, Finland and Norway). These benefitted from the loan guarantee schemes provided under the CIP and MAP programmes in the period 2002-2017. This working paper is based on a report provided by the EIF to the DG for Internal Market, Industry, Entrepreneurship and SMEs of the European Commission under the Direct Service Contract Ares(2017)5414015- 07/11/2017. We refer the reader to the full report for more details on the methodology, robustness tests, and additional analyses. Interested readers can consult the full report here: https://doi.org/10.2873/038836 (Bertoni et al., 2018b henceforth).

The working paper aims to provide reliable econometric findings relating to the following issues:

- Treatment effects.
  - Did benefitting SMEs create more jobs, increase their sales and assets, become more profitable and increase their relative share of intangible assets more than they would otherwise have?
  - Are beneficiary SMEs more likely to survive due to the access to these schemes?
  - Is there any difference in the magnitude of the treatment effect of receipt of guaranteed loans across the three geographical areas under consideration?
- Moderating effects.
  - Is the effect stronger for more financially constrained (i.e. smaller and younger) firms?
  - Does the effect depend on the guaranteed loan amount?
  - Are there differences in the effect across industries?
- Robustness. Are the results robust to controls for non-parallel growth, credit events and sample selections? What is the impact on the "extensive growth" (rather than growth rate) of companies?

The study focuses on a population of174,107 loans, corresponding to a total loan amount of EUR 15.58 billion. The econometric analysis is carried out only on the loans received by limited liability companies for which accounting data were available in Bureau van Dijk's Orbis database. These firms account for 45,984 firm-year observations and EUR 8.23 billion of guaranteed loans received. For sole proprietorships and partnerships, accounting data are generally unavailable. We present a specific analysis on sole proprietorships in section 3.1.7.

We estimate the "conditional" average treatment effect on the treated (ATT, "treatment effect" henceforth) of the receipt of these loans by beneficiary SMEs in a five-year period around the granting of the guaranteed loan. In order to estimate the treatment effect, we rely on matching techniques that combine coarsened exact matching (CEM), propensity-score matching (PSM) and *difference in differences* (dif-in-dif) estimation.

The paper is organised as follows. In Section 2, we first describe the construction of the sample of treated SMEs and the control group of "twin" non-treated SMEs. We then describe our performance measures and the control variables used in the econometric analysis. We finally illustrate the methodology used to estimate the treatment effect. In section 3, we report the results of the estimates of the treatment effect on the different growth measures and the likelihood of survival up until four years after the receipt of the loan. We also report how these treatment effect estimates vary across the three geographical areas under consideration. We then investigate the influence on the treatment effect exerted by firm-level characteristics (i.e. size, age, and industry). Lastly, we report additional evidence on the impact of loan amount on treatment effect. We conclude in Section 4 by summarizing our results and discussing the limitation of our study.

2 Data and methodology

2.1. The population of treated companies

In this section we illustrate the distribution and characteristics of the population of guaranteed loans considered in this study. The term "population" refers to all the units of analysis that would end up in the final sample in the absence of data limitations. The econometric study is based on accounting information, published annually. Accordingly, the effects of different loans obtained in the same year cannot be disentangled. Our unit of analysis will thus be the firm-signature year, corresponding to one or more guaranteed loans received by a specific firm in a given year.

The population of guaranteed loans corresponds to a total of 174,107 units of observations. In 95.24% of cases, beneficiaries received only one loan in a given signature (*i.e.* treatment) year. There are 7,626 cases (4.38%) in which companies received two loans in the same year, and 654 cases in which firms received more than two loans in the same year. These multiple guaranteed loans per signature year are aggregated into the same unit of observation in this descriptive analysis, as well as in the econometric study that we conducted. For simplicity, we refer to these units as "guaranteed loans" or "loans".

Table 1 shows the distribution of loans in the three geographical areas considered in this study, by characteristics of the loan (programme, signature year and loan amount) and by characteristics of the recipient company (age class at the time of the loan, industry, location and legal form).

Table 1: Distribution of guaranteed loans in the three geographical areas by features of the loan[2]

	Total		Italy		Benelux		Nordic	
	N	%	N	%	N	%	N	%
Distribution by programme								
CIP	64,983	37.32	59,189	39.36	5,794	51.27	0	0.00
MAP	109,109	62.67	91,181	60.63	5,507	48.73	12,421	100.00
CIP and MAP	15	0.01	15	0.01	0	0.00	0	0.00
Total	*174,107*	*100.00*	*150,385*	*100.00*	*11,301*	*100.00*	*12,421*	*100.00*
Distribution by signature year								
2002-2003	15,399	8.84	12,584	8.37	53	0.47	2762	22.24
2004-2005	50,609	29.07	42,285	28.12	2,845	25.17	5479	44.11
2006-2007	42,524	24.42	35,532	23.63	2,815	24.91	4177	33.63
2008-2009	9,437	5.42	7,928	5.27	1,506	13.33	3	0.02
2010-2011	26,785	15.38	25,442	16.92	1,343	11.88	0	0.00
2012-2013	18,267	10.49	17,405	11.57	862	7.63	0	0.00
2014-2015	10,281	5.90	8,867	5.90	1,414	12.51	0	0.00
2016-2017	805	0.46	342	0.23	463	4.10	0	0.00
Total	*174,107*	*100.00*	*150,385*	*100.00*	*11,301*	*100.00*	*12,421*	*100.00*
Distribution by loan amount (EUR thousands, 2010 prices)								
< 25	52,172	29.97	46,043	30.62	1,716	15.18	4,413	35.53
25 - 50	50,059	28.75	45,293	30.12	2,344	20.74	2,422	19.50
50 - 100	34,527	19.83	30,124	20.03	2,134	18.88	2,269	18.27
100 - 500	32,970	18.94	25,283	16.81	4,849	42.91	2,838	22.85
> 500	4,379	2.52	3,642	2.42	258	2.28	479	3.86
Total	*174,107*	*100.00*	*150,385*	*100.00*	*11,301*	*100.00*	*12,421*	*100.00*

About two thirds of the population of guaranteed loans belong to the MAP programme and one-third to the CIP programme.[3] Most (150,385, corresponding to 86.2% of the population) of the loans are granted to companies located in Italy. The remaining part of the population is almost

[2] Unless stated otherwise, all tables/figures are authors' elaborations, based on EIF and Orbis data.
[3] Note that in 15 cases (0.01%) a company received guaranteed loans from both programmes in the same signature year.

equally split between Benelux and the Nordic countries. Both CIP and MAP loans are observed in Italy and Benelux, whereas only MAP loans are observed in the Nordic countries.

The reason for this difference is that in the Nordic countries the guaranteed loan scheme was active only in the early years of our observation window, as illustrated in the distribution of loans by signature year. Loans in the Nordic countries are concentrated between 2002 and 2007. The time distribution of loans is qualitatively similar between the other two geographical macro-regions (Italy and Benelux) and spans the whole period 2002-2017. If we look at the overall population, we observe that loans for the first period (2002-2007) represent 62%, and the remaining 38% is distributed over the period 2008-2017.

One interesting dimension is the distribution of loans by their amount.[4] At the two extremes, 30% of the loans have a principal amount below EUR 25,000 and 2.5% of the loans have a principal amount above EUR 500,000. The category including small loans is more populated in Italy (30.6%) and the Nordic countries (35.5%) than in Benelux (15.2%). The category composed of the largest loans is more populated in the Nordic countries (3.9%) than in Italy (2.4%) and Benelux (2.3%).

In summary, the distribution of guaranteed loans by signature year and amount confirms that the support of the population is large (i.e., we have numerous observations across all periods and loan amounts), with the exception of the Nordic countries, where loans are only observed in the first period. On the other hand, the distribution also illustrates some differences across countries (e.g., in the breakdown by amount), which will have to be accounted for in order to compare the impact of the programmes across different macro-regions.

As shown in Table 2, guaranteed loan beneficiaries are on average young but, again, there are noteworthy differences across geographical macro-regions. A substantial portion (19.0%) of the guaranteed loan beneficiaries are companies that are 1 year old or younger. This fraction is higher in Benelux (57.5%) and the Nordic countries (38.6%) than in Italy (14.5%). Similarly, the fraction of beneficiaries that are older than 25 years, which is 10.4% in the global population, is larger in Italy (11.5%) than in Benelux (3.0%) and the Nordic countries (3.3%).

In terms of industry distribution, 26.6% of the loan beneficiaries operate in manufacturing (section C of NACE classification). This fraction is similar across Italy (28.2%) and the Nordic countries (25.7%), but it is much smaller in Benelux (7.7%). Construction (NACE section F), which represents instead 17.2% of the overall population, is substantially larger in Italy (19.2%) than in Benelux (6.5%) and the Nordic countries (5.2%).

The geographical distribution of beneficiaries across NUTS-1 regions is broadly consistent with the economic relevance of the different regions.[5] Most NUTS-1 regions include an adequate number of beneficiary firms, even if there are a few NUTS-1 regions with a very small number of observations (e.g. LU0 - Luxembourg, 3 observations and FI2 - Åland islands, 2 observations).

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[4] To allow for a consistent comparison of monetary amounts over time, all loan amounts have been deflated using GDP price deflators and are indexed to the year 2010.

[5] This paper distinguishes regions (sub-national administrative areas) from (supra-national) macro-regions. The terms macro-region and geographic area are used interchangeably.

Table 2: Distribution of guaranteed loans in the three geographical areas by characteristics of the companies

	Total		Italy		Benelux		Nordics	
	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)
Distribution by age class								
< 1 year old	33092	2270	21801	1159	6503	675	4788	437
1-5 years old	55275	4251	47980	3408	3080	433	4215	410
6-25 years old	67669	6677	63290	6044	1376	201	3003	432
> 25 years old	18067	2384	17310	2259	342	60	415	65
Total	*174103*	*15582*	*150381*	*12869*	*11301*	*1368*	*12421*	*1344*
Distribution by industry								
Construction (F)	22921	1326	21704	1205	574	47	643	73
Manufacture (C)	35386	4576	31515	4165	686	89	3185	322
Trade (G)	23222	2148	17631	1565	2750	304	2841	280
Other	51411	4900	40791	3584	4874	648	5746	669
Total	*132940*	*12950*	*111641*	*10518*	*8884*	*1088*	*12415*	*1344*
Distribution by region								
ITC	66556	5790	66556	5790				
ITF	3658	558	3658	558				
ITG	966	177	966	177				
ITH	33607	3329	33607	3329				
ITI	45342	2964	45342	2964				
BE1	951	73			951	73		
BE2	3237	308			3237	308		
BE3	3079	245			3080	245		
NL1	465	77			465	77		
NL2	980	185			980	185		
NL3	1658	299			1658	299		

Table 2 continued

	Total		Italy		Benelux		Nordics	
	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)	Nr. of loans	Amount of loans (EUR m)
NL4	927	182			927	182		
LU0	3	0			3	0		
DK0	655	159					655	159
FI1	2864	719					2864	719
FI2	2	1					2	1
NO0	46	12					46	12
SE0	6	0					6	0
SE1	2939	174					2939	174
SE2	3910	179					3910	179
SE3	1831	96					1831	96
Total	*173682*	*15526*	*150129*	*12818*	*11301*	*1368*	*12253*	*1339*
Distribution by legal form								
Private limited	43109	7081	31407	5465	4653	744	7049	871
Public limited	2875	1150	1725	988	345	65	805	97
Partnerships	32400	2263	30984	2111	908	122	508	31
Sole proprietorships	53517	2213	48767	1995	3148	164	1602	54
Other forms	194	60	169	55	12	2	13	3
Total	*132095*	*12767*	*113052*	*10613*	*9066*	*1097*	*9977*	*1057*

Note: discrepancies in "Total" rows indicate data loss following the pairing of EIF data with Bureau Van Dijk's Orbis data.

Finally, in terms of legal form, about one third of companies have limited liability (32.6% are private limited liability companies and 2.2% are public limited liability companies). The largest category of legal status for beneficiaries is Sole proprietorships, which represent 40.5% of the total population. Partnerships are 24.5% of the population of beneficiaries. It is important to note that the breakdown by legal form is substantially different across geographical areas. Sole proprietorships represent 43.1% of the Italian population, 34.7% of the Benelux population, but only 16.1% of the population in the Nordic countries. Symmetrically, public and private limited companies are 29.3% in Italy, 55.1% in Benelux and 78.7% in the Nordic countries. As we discuss below, this substantially affects the data availability in each of the three geographical areas.

Table 2 also illustrates the distribution of the population weighted by the size of the loans. The distribution of the population is overall very similar in terms of loans and loan amounts and, for the sake of brevity, we will only focus here on the few substantial differences that are observed when weighting the loans by size. First, when we look at the age distribution of firms, we see that whereas young firms (1 year or less) represent a larger category than old firms (25+ years) in terms of number of observations (19.0% vs. 10.4%), the opposite is true when we look at loan amounts (14.6% vs. 15.3%). This is not surprising, considering that older firms are also, on average, larger and, consequently, receive on average larger loans.

Second, and similarly, the relevance of sole proprietorships is substantially reduced when we look at the Euro-weighted distribution. Limited liability companies, which are responsible for 34.8% of loans, receive 64.5% of the total loan amount. Sole proprietorships, which represent 40.5% of beneficiaries, receive only 17.3% of the total amount. In summary, while sole proprietorships represent a substantial number of loans (and the single largest category of recipients), these loans are on average small, and their value-weighted importance is modest. Lastly, when we consider the loan amount, the weight of manufacturing increases by almost ten percentage points, to the detriment of construction.

2.2. Focus on limited liability companies

Data might not be available for all firms and years. Therefore, the econometric study is conducted on a sample of firms, rather than on the whole population described in the previous section. Ideally, the final sample would be sufficiently large and randomly extracted from the population. The size of the sample determines the precision of the estimates (larger samples resulting in smaller confidence intervals for the estimated parameters). The randomness of the extraction ensures that these estimates are unbiased with respect to the true values of the underlying population. We further put to the test this fundamental assumption through the robustness checks presented in Appendix I.

Accounting data were retrieved from the Bureau Van Dijk's Orbis database.[6] In order to retrieve accounting figures, we carried out an identification process for each beneficiary. However, many beneficiary firms could not be identified in the Orbis database. Specifically, in the population of 174,107 guaranteed loans (corresponding to EUR 15.58 billion of guaranteed loans), only 75% (and 80% of the loans by amount) were granted to beneficiaries that are identifiable in Orbis. For these firms we have basic information (e.g., NUTS1 region, industry, date of incorporation) but no

[6] https://orbis.bvdinfo.com [Last accessed: September 2018].

complete accounting data. Overall, sufficient accounting data is available for 45,365 loans (EUR 7.3 billion EUR), corresponding to 26% of the population (47% in terms of loan volumes). Table 3 reports the results of the identification process. Further details are discussed in Bertoni et al. (2018b).

Table 3: Share of guaranteed loans by identification strategy and outcome

Outcome	Macro-Area			
	Italy	Benelux	Nordic countries	All macro-regions
Identified based on tax code	76%	49%	64%	*74%*
Identified based on business entity	0%	31%	17%	*3%*
Unidentified	24%	20%	19%	*23%*

Most (78.65%) of the loans for which we have some accounting data were granted to limited liabilities firms, while loans granted to sole proprietorships and partnerships represent a minority (11.81% and 9.31%, respectively). In fact, in most European countries, sole proprietorships and partnerships either do not file their financial accounts or, if they do, they file simplified accounts that do not include the variables needed to perform our analysis.

Therefore, we decided to restrict our econometric analysis to loans granted to limited liability companies. Sole proprietorships are on average smaller than limited liability companies, and receive smaller loans. They also have no limited liability and no deposited capital, which makes the due diligence process of the bank (and the possibility of loan recovery) substantially different for these beneficiaries. We hence cannot assume that the impact of guaranteed loans on sole proprietorships is the same as for limited liability companies, nor we can predict if it would be greater or lower.

The population of treated limited liability companies represents 45,984 firm-year observations for a total of EUR 8.23 billion of guaranteed loans received. We have accounting data for 35,674 firm-years, equivalent to 78% of the population, receiving EUR 6.75 billion of guaranteed loans, representing 82% of the amount received by all limited liability companies.

Our final sample is further restricted because of two additional requirements. First, information on several variables in the year before signature year needs to be available to match the beneficiary to a non-beneficiary "twin". Specifically, our matching algorithm is based on the following pre-event variables (or ratios built using these variables) measured at the beginning of the signature year t: the dependent variable of interest (total assets, sales or employment costs), country, industry (NACE 2 digits), age, short term debt, long term debt, cash and intangible fixed assets. Second, information relative to the dependent variable needs to be available T years after the beginning of the signature year (t+T) in order to study the T-year growth in the dependent variable. As we explain in the following, T varies between 0 and 4. This means that for the same dependent variable (e.g. assets) we will have different samples for different values of T. In general, more companies will enter into the sample for smaller values of T (short-period growth) than for larger values (long-period growth).

For example, let us illustrate how the number of observations varies when we look at total assets as dependent variable. Information on all matching variables including total assets is available at time t (the beginning of the signature year) for 26,487 firm-year observations (or EUR 5.46 billion), i.e., 58% of the population of limited liability companies (or 66% in terms of value of the loans). To analyse total assets growth *during the signature year*, we will be able to use information on 24,541 firm-year observations (EUR 5.17 billion), i.e., 53% of the population (63% in value). For *the first year after the end of the signature year*, the fraction goes down to 50% (60% in value), for the second year after treatment it is 45% (55% in value) and for *the third year after the signature year* it is 39% (51% in value). We decided to use *the fourth year after the end of the signature year* as the longest observation window. With such criteria, we are still able to observe a large number of loans (34%, or 46% in value) corresponding to 15,806 beneficiaries, which are generally sufficient to obtain reliable estimates.[7] The coverage of this final sample with respect to the original population of treated limited liability companies strongly varies across geographical macro-regions. In Italy, it is 42% (54% in terms of value); in Benelux, it is only 4% (2% in terms of value) and in the Nordic countries it is 23% (24% in terms of value). Table 4 summarises the data loss at each step.

Table 4: Firms and loan amounts (EUR 2010 million) available by analysis step and macro-region

	All macro-regions		*Italy*		*Benelux*		*Nordics*	
	N loans (%)	*Amount in EUR m (%)*	*N loans (%)*	*Amount in EUR m (%)*	*N loans (%)*	*Amount in EUR m (%)*	*N loans (%)*	*Amount in EUR m (%)*
Limited liabilities	45,984 (100%)	8231 (100%)	33,132 (100%)	6453 (100%)	4,998 (100%)	809 (100%)	7,854 (100%)	969 (100%)
Accounting data	35,674 (78%)	6752 (82%)	27,520 (83%)	5698 (88%)	2,746 (55%)	478 (59%)	5,408 (69%)	576 (59%)
PSM "Matchable"	26,487 (58%)	5465 (66%)	23,467 (71%)	5079 (79%)	644 (13%)	93 (11%)	2,376 (30%)	294 (30%)
Assets in t=0	24,541 (53%)	5165 (63%)	21,903 (66%)	4826 (75%)	509 (10%)	68 (8%)	2,129 (27%)	271 (28%)
Assets in t=1	22,960 (50%)	4906 (60%)	20,575 (62%)	4601 (71%)	364 (7%)	45 (6%)	2,021 (26%)	260 (27%)
Assets in t=2	20,494 (45%)	4559 (55%)	18,281 (55%)	4280 (66%)	261 (5%)	27 (3%)	1,952 (25%)	253 (26%)
Assets in t=3	17,946 (39%)	4162 (51%)	15,838 (48%)	3894 (60%)	229 (5%)	23 (3%)	1,879 (24%)	245 (25%)
Assets in t=4	15,806 (34%)	3757 (46%)	13,786 (42%)	3501 (54%)	192 (4%)	19 (2%)	1,828 (23%)	237 (24%)

Note: total assets chosen as the reference variable. Results may vary when using a different financial indicator.

2.3. The initial control group: stratified random sampling

As explained in detail below, the counterfactual analysis used in this study entails the comparison of the performance of treated companies with the performance of companies that were not treated, but that presented similar characteristics. We refer to these twin companies as the "control group".

To identify an appropriate control group, we first downloaded from Orbis the data of all companies that had similar characteristics to the treated companies. To do so, we first classified the treated companies in "strata", i.e., groups of companies that presented homogeneous characteristics before the signature of the loans.

[7] Longer observation periods, such as T=10, would make the sample shrink to only 15% of the total number of beneficiaries (21% in value).

We used the following four main stratifying variables:

a) NUTS-1 region (20 regions),[8]
b) NACE Rev. 2 main industry division (i.e. 20 industries),[9]
c) time period, and
d) legal form.

The "time" bracket refers to three main time intervals accounting for the foundation years of firms from the specific stratum. We distinguish between the firms founded:

a) before 1991,
b) between 1991 and 2000,
c) between 2001 and 2005,
d) and between 2006 and 2016.

Concerning the legal forms, sole proprietorships were initially excluded from the treatment group's initial population due to data availability issues. Therefore, two strata were considered:

a) "Private limited companies" or "Public limited companies", and
b) "Partnerships".[10]

Combining these different criteria makes a total of 1,525 strata with at least one treatment firm. Focusing the attention on limited companies only further reduces the number of strata to 947. To minimise the burden with respect to data extraction, we excluded from the initial pool of counterfactual firms those that were flagged by Orbis as providing "no financials".

To retrieve all control candidates for each stratum, we faced a trade-off in terms of a) the extraction costs in terms of time and b) the expected accuracy of the matching method. On average, Orbis provided us with 375 control candidates per treated firm. Retrieving all such candidates (almost 30 million firms) would require significant time, but obtaining too few of these may negatively affect the matching model, which would be selecting suitable controls from a restricted initial set.

Following some sample-based tests and various experiences from the literature, we chose an initial ratio of 15 control candidates per loan. For each stratum, we randomly selected a number of control candidates equivalent to 15 times the number of loans in the same stratum. In 7.5% of the strata, Orbis could provide us with less than 15 control candidates per loan. Overall, we obtain a final initial counterfactual group composed of 973,730 firms, for which we downloaded accounting data in the period 2001-2017.

[8] BE1, BE2, BE3, DK0, FI1, FI2, ITC, ITF, ITG, ITH, ITI, NL1, NL2, NL3, NL4, NO0, SE0, SE1, SE2, SE3.
[9] A - agriculture, forestry and fishing; B - mining and quarrying; C - manufacturing; D - electricity, gas, steam and air conditioning supply; E - water supply; sewerage, waste management and remediation activities; F - construction; G - wholesale and retail trade, repair of motor vehicles and motorcycles; H - transportation and storage; I - accommodation and food service activities; J - information and communication; K - financial and insurance activities; L - real estate activities; M - professional, scientific and technical activities; N - administrative and support service activities; O - public administration and defence, compulsory social security; P - education; Q - human health and social work activities; R - arts, entertainment and recreation; S - other service activities; U - activities of extraterritorial organisations and bodies.
[10] Partnerships were later excluded from the analysis due to poor data coverage. See section 2.2.

2.4. Performance measures and controls

We evaluated the treatment effect of guaranteed loans on a number of dimensions of firm performance. [11] Namely:

- The growth of total assets;
- The growth of sales;
- The growth of employment, measured via employment costs; [12]
- The relative change in profitability, measured as the growth of profits before taxes; [13]
- The growth in innovativeness, measured via intangible fixed assets over total assets;
- Survivorship, measured as a dummy equal to 1 if the company was dissolved at time t.

Growth estimates are based on accounting variables retrieved from Orbis for the period 2002-2016. We deflate all accounting variables using country and sector-specific producer price indices (at the level of NACE Rev. 2 divisions, see footnote 9) with base year 2010, collected from national statistical offices. All growth measures are winsorised at 1% to limit the impact of outliers. For survival, we retrieved information on the status of companies at the end of the observation period (early 2018) from the Orbis database. In case of dissolution, Orbis provides the date of the event.

We also consider several moderators of the impact of the loans on growth models.

- Age and size: the literature suggests that smaller and younger companies are the most financially constrained. Therefore, they are likely to benefit more from guaranteed loans.
- Loan amount: we expect that bigger loans result in a bigger improvement in the performance of the beneficiaries.
- Industry: The effect of loans on beneficiaries may vary across industries.

2.5. Descriptive statistics

Table 5 shows summary statistics on our full sample of treated and non-treated companies (before matching). We consider five measures related to performance: sales, employment, assets, asset intangibility and profitability. Measures are computed the year before treatment for treated companies, and in all available years for non-treated companies. Before matching, and despite the random stratified sampling strategy used, treated companies on average tend to be younger than non–treated. They are also smaller in terms of assets, employment and sales, less profitable and with a higher share of intangibility. Such differences should be reduced after matching the two sets.

Table 6 provides detailed information on treated companies. Some interesting differences emerge: recipients of CIP guaranteed loans tend to be smaller and less profitable than recipients of MAP

[11] Whenever possible, we employed log-transforms of variables to setup a log-linear model. In this setting, the treatment effect coefficient represents the instantaneous increase of the rate of growth for the outcome variable due to a change in treatment status (i.e. treated/untreated).

[12] Employment growth is better measured using cost of employment than number of employees in our setting. The number of employees is a data field in Orbis that has relatively poor quality and is not regularly updated, especially for SMEs. Employment cost also captures changes in full-time equivalent terms beyond what would be possible from a simple headcount. We use a full set of industry and time dummies, capturing systematic changes in salaries that are not related to job creation. Nevertheless, our robustness check using headcount (not reported) reveals qualitatively similar results.

[13] To account for negative profits, we used the neg-log transformation.

Table 5: Descriptive statistics of treated and un-treated companies before matching.

	Treated				Non-treated (all)			
	mean	median	sd	N	mean	median	sd	n
Age (in years)	9.48	5	12.5	40746	14.42	11.00	12.90	5017794
Total Assets (in EUR k)	2443.86	909.65	4977.74	28571	7938.91	514.50	457792.00	4964784
Employment (in EUR k)	2704.17	1057	5992.26	27210	6609.42	482.15	365461.70	4507433
Sales (in EUR k)	458.51	221	719.069	25167	863.59	148.69	646192.90	3541290
Intangibility (%)	0.07	0.014	0.128	28368	0.04	0.00	0.13	4797620
Profitability (in EUR k)	48.23	18.42	297.864	27935	270.46	10.08	199315.00	4781173

and have relatively more intangibles. Also, larger loans are given to larger and more profitable companies. Older companies tend of course to be larger and more profitable, and have less intangible assets. Companies in manufacturing are larger than other companies. Older companies and public limited liability companies are also larger and more profitable than their counterparts.

Interesting differences emerge across geographical macro-regions in terms of treated firms' attributes in the signature year. Beneficiaries in Italy were bigger in assets, employment and sales than beneficiaries in Benelux and Nordics. Italian beneficiaries were also strikingly more profitable than in the other countries, while asset intangibility was comparable across the three macro regions.

Table 6: Descriptive statistics of treated companies. All values in logs, unless specified.

Sample	Total Assets		Empl. costs		Sales		Profitability		Asset intangibility (%)	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	Mean	std. dev.
All treated firms	6.76	1.56	5.18	1.70	6.91	1.60	1.81	3.35	0.06	0.13
by program										
MAP	7.37	1.42	5.69	1.49	7.39	1.51	2.17	3.69	0.06	0.13
CIP	7.01	1.29	5.22	1.60	6.94	1.42	1.96	3.16	0.08	0.12
by signature year										
2002-2003	6.95	1.63	5.58	1.51	7.24	1.60	1.96	3.57	0.05	0.12
2004-2005	6.90	1.53	5.32	1.62	7.05	1.58	2.00	3.42	0.06	0.12
2006-2007	6.98	1.51	5.28	1.71	7.07	1.58	2.11	3.45	0.06	0.12
2008-2009	6.67	1.60	4.99	1.83	6.74	1.65	1.54	3.34	0.07	0.13
2010-2011	6.47	1.57	4.86	1.77	6.55	1.63	1.82	3.01	0.08	0.14
2012-2013	6.42	1.44	4.78	1.74	6.51	1.43	1.24	3.09	0.08	0.14
2014-2015	6.47	1.51	4.96	1.69	6.84	1.50	1.64	3.12	0.08	0.15
2016-2017	7.44	1.17	6.01	1.63	7.28	1.20	3.53	2.57	0.04	0.10
by loan amount (EUR k, 2010 prices)										
< 25	5.62	1.04	4.17	1.61	5.84	1.29	0.79	2.88	0.06	0.14
25 - 50	6.24	0.98	4.72	1.45	6.36	1.17	1.55	2.88	0.07	0.14
50 - 100	6.71	0.96	5.08	1.42	6.70	1.27	1.48	3.32	0.08	0.15
100 - 500	7.82	1.08	6.00	1.28	7.80	1.24	2.58	3.61	0.07	0.11
> 500	8.86	0.97	6.76	1.15	8.60	1.32	3.25	4.18	0.05	0.09

Table 6 continued

Sample	Total Assets		Empl. costs		Sales		Profitability		Asset intangibility (%)	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.	Mean	std. dev.
by age class										
< 1 year old	5.09	1.55	3.26	1.90	4.87	1.65	0.06	2.66	0.12	0.19
1-5 years old	6.20	1.35	4.58	1.65	6.37	1.46	1.42	3.15	0.09	0.15
6-25 years old	7.11	1.38	5.49	1.49	7.25	1.39	2.22	3.31	0.05	0.10
> 25 years old	7.87	1.31	6.22	1.25	7.89	1.32	2.38	3.86	0.03	0.06
by industry										
Construction (F)	6.71	1.45	5.11	1.59	6.77	1.43	2.51	2.73	0.02	0.06
Manufacture (C)	7.24	1.41	5.69	1.45	7.34	1.41	2.25	3.44	0.05	0.09
Trade (G)	6.58	1.52	4.60	1.76	6.95	1.62	1.58	3.19	0.06	0.11
Other	6.20	1.62	4.74	1.84	6.23	1.71	1.04	3.38	0.11	0.18
by macro-region										
Italy	6.99	1.47	5.28	1.67	7.05	1.53	2.07	3.28	0.06	0.11
Benelux	5.67	1.51	3.82	2.03	5.65	1.83	0.44	3.45	0.08	0.20
Nordics	5.61	1.45	4.68	1.69	5.99	1.75	0.33	3.36	0.07	0.18

Note: the table portrays pre-treatment averages and standard deviations of all financial indicators. All financial variables are deflated using producer price indices at the level of NACE Rev. 2 divisions.

2.6. Empirical approach

In order 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 guaranteed loans (treated) with the outcome of the same companies *had they not received the loan*. These outcomes are *potential*, in that only one of the two is observable after the treatment is administered. Formally, if D=1 indicates the treatment variable, we refer to Y^1_{post} as the potential outcome after the treatment if the company was treated, and to Y^0_{post} as the potential outcome after the treatment if the company was not treated. The mean causal effect is captured by the Average Treatment Effect on the Treated (ATT) at time t, defined as:

$$ATT_{post}=E\left[Y^1_{post}\text{-}Y^0_{post}|D=1\right] \tag{1}$$

When the treatment is not randomly assigned, as in our case, we can improve identification by controlling for the covariates X explaining the probability of treatment of that company. In this case:

$$ATT_{post}=E\left[Y^1_{post}\text{-}Y^0_{post}|X=x,D=1\right] \tag{2}$$

Clearly, $Y^0_{post}|D=1$ is unobservable, hence it is referred as the "potential outcome" in Rubin's Causal Model (Rubin, 1974). Under some key assumptions (discussed in Bertoni et al., 2018b), an appropriate control group of untreated companies can replace $Y^0_{post}|D=1$ to compute the ATT.

In this study, we implement the potential outcome framework via the *difference in differences* (dif-in-dif, DD) technique. This approach is applicable when information on the outcome before the treatment, i.e., Y_{pre}, is available to the researcher. The idea of the dif-in-dif is to first compute the difference in outcome between treated and controls after the treatment. From this, one further subtracts any potential outcome difference that can be observed *before* the treatment took place. Expressing the ATT in the case of the dif-in-dif introduces a certain number of assumptions (Lechner, 2010). The reader is referred to Bertoni et al. (2018b) for further details.

The core assumptions of the dif-in-dif approach allow rewriting the ATT as follows:

$$ATT=E\left[Y^1_{post}\text{-}Y^0_{post}|X=x,D=1\right]= \\ =E\left[Y^1_{post}\text{-}Y^1_{pre}|X=x,D=1\right]\text{-}E\left[Y^0_{post}\text{-}Y^0_{pre}|X=x,D=0\right] \tag{3}$$

To produce more accurate estimates, we combine the dif-in-dif approach with the *matching approach*, as recommended by the literature (see e.g. Blundell and Costa Dias, 2000, p.438). The matching approach allows selecting a control group of companies with observable characteristics similar to those of the treated.

If the effect of the treatment is heterogeneous and varies across categories of companies (e.g., by size or age, as we expect), matching on the variables that moderate the effect also guarantees that an appropriate control is selected for all categories of companies, and the ATT can be correctly estimated (Blundell et al., 2004). Moreover, Lechner (2010, p. 191) recommends matching on past outcomes (Y_{pre}) to reduce biases due to violations in the assumptions.

The main assumption of matching estimators is that they satisfy unconfoundedness (Stuart 2010). This assumption requires that the treatment assignment is independent of the potential outcomes, given the covariates X. In other terms, this supposes that there would be no unobserved endogenous variable that simultaneously explains outcome and treatment assignment. This assumption is further discussed in Bertoni et al. (2018b).

Should the matching procedure satisfy the unconfoundedness assumption, further conditioning on X would not be needed (Rosenbaum & Rubin, 1983). However, conditioning may correct for bias if some imbalance is still present between treated and matched companies. Henceforth, our final estimator for the treatment effect is a “conditional” ATT, in that it estimates the ATT in a regression setting that further controls for X.

Our choice of the matching variables is highly inspired by the work of Kremp and Sevestre (2013) which explicitly models the demand and supply of credit to (French) SMEs. They emphasise the importance of the size of the companies (here captured by the lagged outcome variable) and risk factors (i.e., leverage, liquidity, intangibility and age). The matching methodology used in this work also has the merit of maintaining comparability with the previous studies Asdrubali and Signore (2015) and Bertoni et al. (2018a) studying the impact of EIF guaranteed loans respectively in CEESE countries and in France.

To identify matched companies, we use the following two-step procedure. For each outcome variable Y, for each year in which we have a loan and for each country in which the company is located, we do the following:

a. Perform a coarsened exact matching (CEM) on companies for which ΔY_{t+T} is available using the following characteristics:

- Y_{t-1} which is the level of Y in the year before the treatment
- the age of the company (in logarithms)
- the industry of the company (NACE rev., 2 digits)

b. Perform a 1-to-1 nearest-neighbour propensity score matching (PSM) without replacement, imposing common support on the companies that are left after the CEM. The Propensity Score is calculated using a probit model with the same variables as the CEM, plus:
   - the short term leverage, computed as the ratio of current debt on assets, winsorised at the 1% level;
   - the long term leverage, computed as the ratio of long term debt on assets, winsorised at the 1% level;
   - the liquidity, computed as the ratio of cash on assets, winsorised at the 1% level;
   - the intangibility, computed as the ratio of intangible assets on total assets, winsorised at the 1% level.

Note that because the matching is carried out by year and country, treated and matched companies are perfectly matched along these two dimensions. The fact that we match separately by signature year implies that the outcome variable is measured in the same actual years for the treated and control. This ensures that macroeconomic trends do not influence our estimate of the ATT.

PSM is a quite standard matching method in the literature, especially in combination with the dif-in-dif methodology (e.g., Blundell et al., 2004; Heckman et al., 1997). CEM is a method developed to overcome the balancing issues of PSM (Iacus, King, & Porro, 2012). Contrary to PSM, CEM allows an ex-ante control of the balancing of the matched sample.

To test the robustness of our approach, we also perform all the analyses using a number of alternative estimation techniques, namely:

- "No matching" (only stratified random sampling)
- 1-step propensity-score matching
- 1-step coarsened exact matching

The results are overall comparable across different methods, which is reassuring with respect to the robustness of our results to the selection of the matching method. A commented example of the robustness checks is provided in Box 1.

Box 1: A detailed example of the use of the CEM and PSM methodology

We report here an example of application of the CEM followed by PSM matching, used to estimate the treatment effect on assets growth T=3 years after a guaranteed loan is received in t=2013 in Italy.

First, the CEM creates categories for each level of coarsened total assets in 2012, age and industry in Italy. Overall the companies for which we have all variables in *Z* and for which we can calculate ΔY_{t+T} are:

- 72 treated companies
- 19,500 untreated companies

CEM generates a total of 2,494 potential strata, out of which 55 are populated by both treated and control group companies. CEM generates the outcome described in the table below.

Box 1 continued

Table: CEM on 3-year assets growth for loans in 2013

Category	Untreated	Treated
All	19,500	72
Matched	1,578	67
Unmatched	17,922	5

Out of the 19,500 untreated companies, 17,922 are dropped because they belong to strata in which no treated companies are present. In other words, these companies have a combination of characteristics that does not describe any treated company. Similarly, 5 treated companies are dropped because there is no untreated company in our sample that has a combination of characteristics that resembles those of these 5 treated companies. CEM hence leaves us with a sample of 67 treated companies and 1,578 untreated companies that exhibit similar pre-treatment characteristics.

We then perform PSM 1-to-1 nearest neighbour matching on the companies that are matched by the CSM. For this purpose, we estimate propensity score using a probit model and identify, among the 1,578 untreated companies matched by the CEM, the 67 companies that have a propensity score that is closest to that of treated companies matched by CEM.

3 Results

3.1. Overall results

This section illustrates the main results of our analysis. For the sake of brevity, we will focus on the results of our baseline approach, *i.e.* coarsened-exact matching and a 1:1 propensity score matching without replacement. Our baseline results, illustrated in Table 7, are broadly consistent to those from alternative methods.

Table 7: Average treatment effect on the treated for five different performance indicators

Treatment year	Total assets	Employment cost	Sales	P/L before tax	Assets intangibility
ATT (T = 0)	0.1563***	0.1279***	0.1198***	0.0164	0.0053***
	(0.003)	(0.0045)	(0.0043)	(0.0279)	(0.0003)
ATT (T = 1)	0.1888***	0.1587***	0.1638***	-0.003	0.0085***
	(0.0044)	(0.0063)	(0.0060)	(0.0317)	(0.0005)
ATT (T = 2)	0.1964***	0.1693***	0.1483***	0.0414	0.0098***
	(0.0055)	(0.0076)	(0.0073)	(0.0342)	(0.0005)
ATT (T = 3)	0.2011***	0.1629***	0.1441***	-0.0587	0.0096***
	(0.0067)	(0.0092)	(0.0089)	(0.0379)	(0.0006)
ATT (T = 4)	0.2055***	0.1582***	0.1446***	-0.0376	0.0098***
	(0.0081)	(0.0105)	(0.0105)	(0.0420)	(0.0007)
Nr. of loans (T = 0)	23,527	21,471	22,804	23,374	23,408

*Note: The table reports treatment coefficients on the CEM+PSM matched sample, controlling for age, industry, macro-region and loan granting year (coefficients omitted). Robust standard errors in brackets. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.*

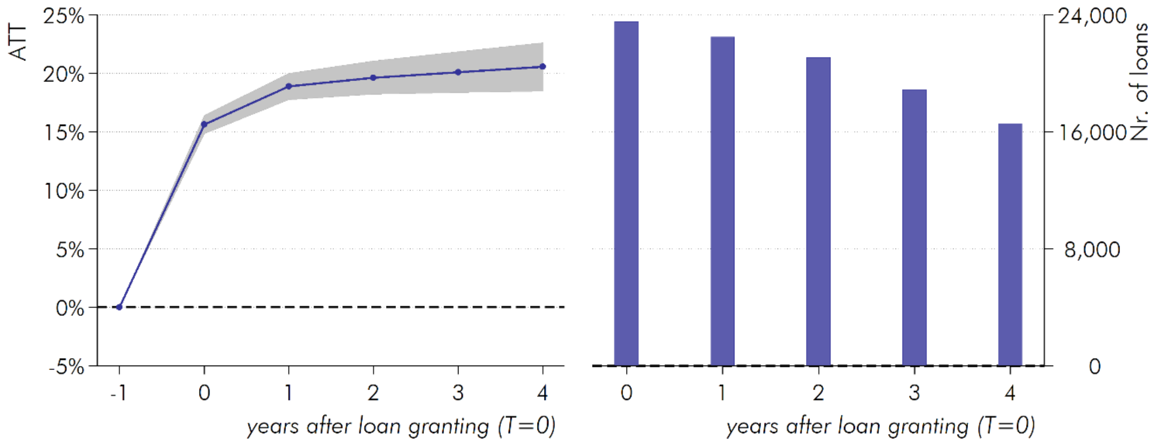
3.1.1. Growth of assets

Figure 1 summarises the estimates for the treatment effect on assets growth, up to the fourth year after treatment. The figure reports the estimated mean treatment effect (blue line) as well as its 99% confidence interval (shaded region). The number of loans (vertical bars, right hand side) is included as well to portray sample size reduction. The estimates are based on a number of loans ranging from 23,527 (treatment year) to 16,581 (fourth year after the signature year).

The results strongly confirm that guaranteed loans have a positive and significant average treatment effect. The effect is positive from the year of the treatment (15.6 percentage points, p-value<1%) and remains positive and significant until the fourth year after treatment (20.5 percentage points, p-value<1%). The confidence interval is relatively tight around the point estimates: in the second year after the end of the signature year, which we take as a general reference point, the estimated average treatment effect is 19.6 percentage points with a 99% confidence interval between 18.2 and 21.1.

Note that growth in total assets is "automatic" once a company receives a guaranteed loan, because the loan will increase current assets (on the asset side of the balance sheet) and financial debt (on the liability side). It is then interesting to verify if the total asset growth we observe is larger than this mechanical growth. The issue is tackled in Appendix I: in short, our analysis supports the existence of growth above and beyond the increase in assets/liability linked to the loan itself.

Figure 1: Estimated treatment effect for total assets



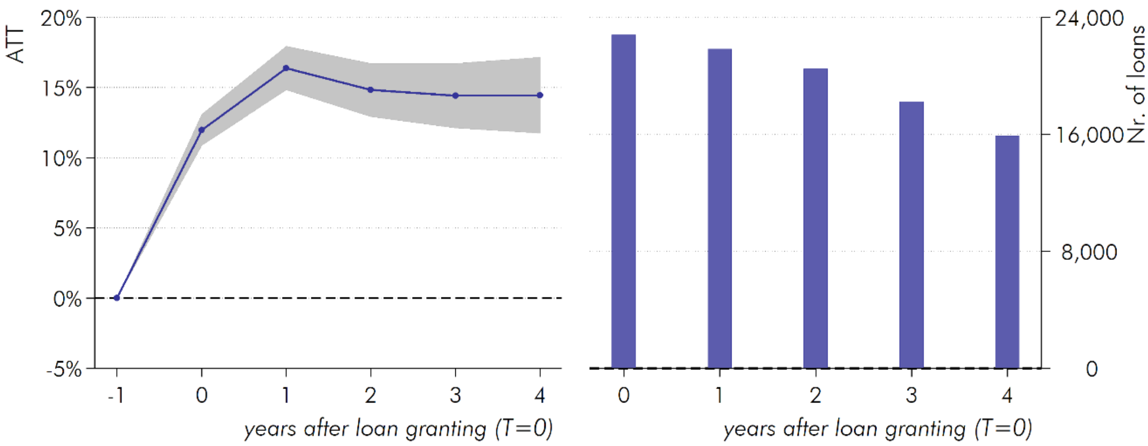
Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on total assets from the treatment year to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The left-hand side of the figure reports the point estimate of the treatment effect as well as the lower and upper bounds its 99% confidence interval (shaded region). On the right-hand side, we plot the number of loans included in each regression.

3.1.2. Growth of sales

Figure 2 reports the estimated treatment effect for sales. The point estimate is positive and significant in each year after the granting of the loan: the estimated treatment effect is 12 percentage points (p-value<1%) in the year of the treatment and 14.5 in the fourth year after treatment. These results confirm that, compared to otherwise similar companies, the beneficiaries of guaranteed loans grow significantly more in terms of sales in the years after the receipt of the loan. The growth in sales seems to be slightly smaller than the growth in assets, but still substantial.

The confidence interval is a bit wider than for total assets. In the second year after treatment the point estimate of the treatment effect is 14.8 and the 99% confidence interval is [12.9, 16.7]. The number of loans included in the analysis ranges between 22,804 (treatment year) to 15,888 (fourth year after treatment).

Figure 2: Estimated treatment effect for sales



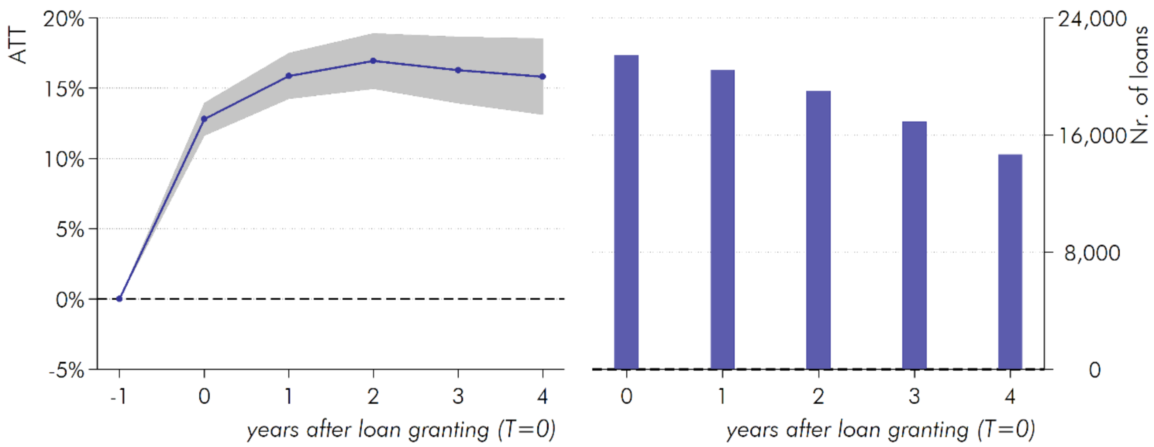
Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on sales from the treatment year to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The left hand side of the figure reports the point estimate of the treatment effect as well as the lower and upper bounds its 99% confidence interval (shaded region). On the right hand side, we plot the number of loans included in each regression.

3.1.3. Growth of employment

We report in Figure 3 the estimated treatment effect for employment costs. The point estimate is positive and significant in each year after the receipt of the loan: the estimated treatment effect is 12.8 percentage points (p-value<1%) in the treatment year and 15.8 in the fourth year after treatment. These results confirm that, compared to otherwise similar companies, the beneficiaries of guaranteed loans grow substantially in terms of employment costs in the years after the receipt of the loan. The growth in employment costs seems to be very similar in magnitude to the growth in sales and slightly smaller than the growth in assets.

The confidence interval is similar to that for sales (and wider than that for total assets). In the second year after treatment the point estimate of the treatment effect is 16.9 percentage points and the 99% confidence interval is [15.0, 18.9]. The number of loans included in the analysis ranges between 21,471 (treatment year) to 14,684 (fourth year after treatment).

Figure 3: Estimated treatment effect for employment costs

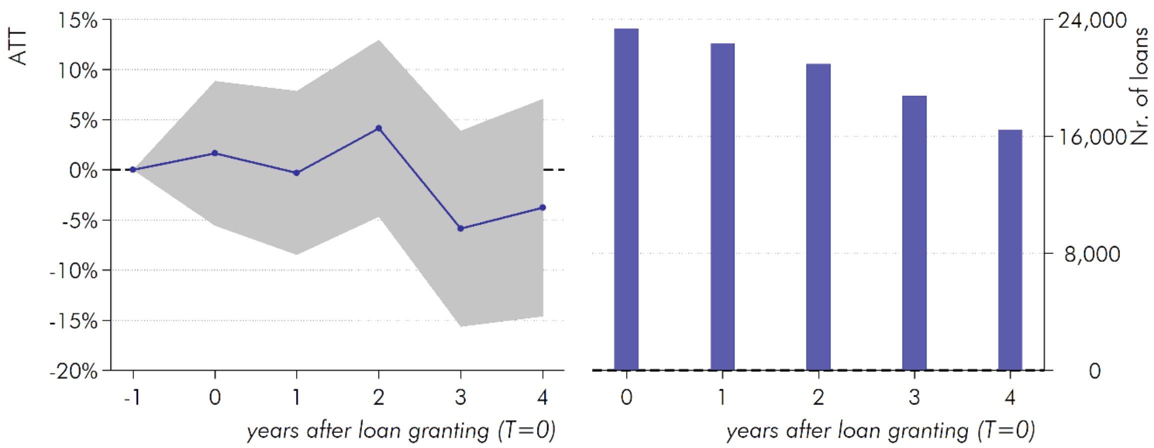


Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on employment cost from the year of the treatment to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The left hand side of the figure reports the point estimate of the treatment effect as well as the lower and upper bounds its 99% confidence interval (shaded region). On the right hand side, we plot the number of loans included in each regression.

3.1.4. Profits

We report in Figure 4 the estimated treatment effect for profits before taxes. The results are markedly different from those illustrated earlier: the estimated treatment effect on profits is close to and never statistically different from zero in any of the five years after the receipt of the loan. These results suggest that the observed growth in output (sales) and inputs (total assets, employment) overall offset each other and leave the bottom line almost unaltered.

Figure 4: Estimated treatment effect for profits



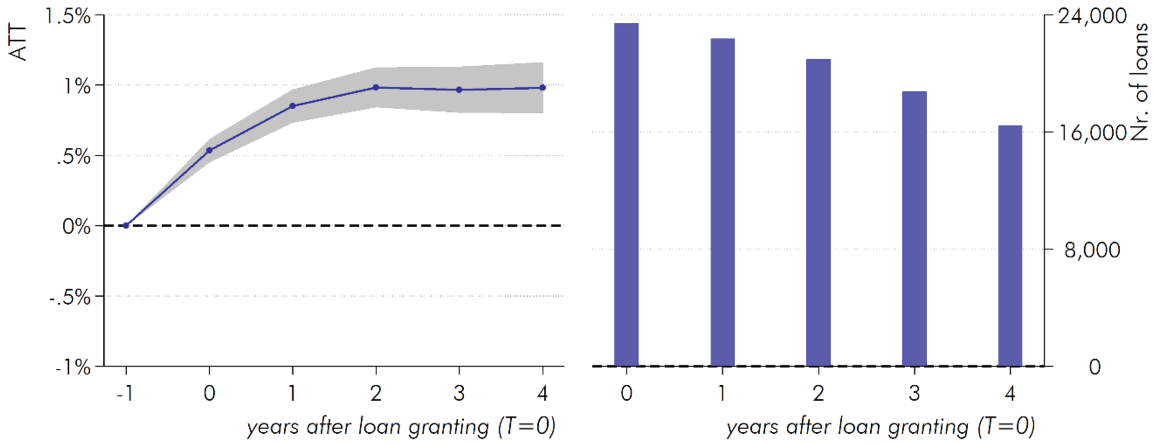
Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on profits before taxes from the treatment year to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The left hand side of the figure reports the point estimate of the treatment effect as well as the lower and upper bounds its 99% confidence interval (shaded region). On the right hand side, we plot the number of loans included in each regression.

The confidence interval is very large. In the second year after treatment the point estimate of the treatment effect is 4.15 percentage points and the 99% confidence interval is [-4.7, 12.9]. It is important to highlight that the confidence interval is larger than that of other variables even if the number of observations is comparable. The number of loans included in the analysis ranges between 23,374 (year of treatment) and 16,454 (fourth year after treatment).

3.1.5. Assets intangibility

Figure 5 illustrates the estimated treatment effect for the ratio of intangible to total assets. The point estimate is positive (albeit small) and significant in each year after the receipt of the loan: the estimated treatment effect is 0.54 percentage points (p-value<1%) during the treatment year and 0.98 in the fourth year after treatment.

Figure 5: Estimated treatment effect for intangible to total assets



Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on intangible to total assets from the treatment year to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The left hand side of the figure reports the point estimate of the treatment effect as well as the lower and upper bounds its 99% confidence interval (shaded region). On the right hand side, we plot the number of loans included in each regression.

These results suggest that, compared to otherwise similar companies, intangible assets, as a fraction of total assets, grew faster for beneficiaries of guaranteed loans. To appreciate the magnitude of the effect, it is important to take into account that the mean ratio of intangible to total assets in our sample is 3.73%, with a median of 0.09% (a large number of companies do not have any intangible assets). The confidence interval is relatively small. In the second year after treatment the point estimate of the treatment effect is 0.99 percentage points and the 99% confidence interval is [0.84, 1.13]. The number of loans included in the analysis ranges between 23,408 (treatment year) and 16,436 (fourth year after treatment).

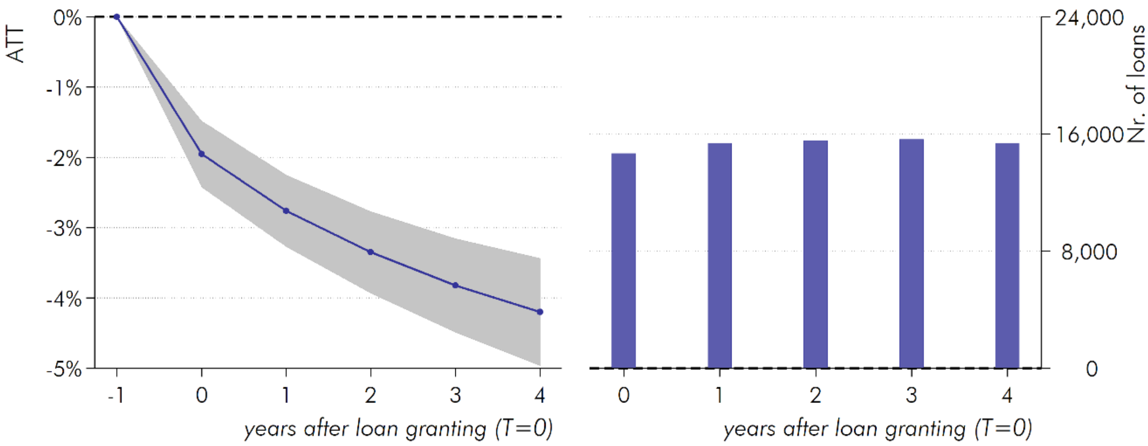
3.1.6. Survival

We report in Figure 6 the estimated treatment effect on the survival of beneficiaries. Specifically, we estimate the probability of dissolution from the treatment year to the fourth year after matching. Also in this case, the control group has been selected with a combination of CEM and PSM. Specifically, for the PSM we used the usual matching variables, and total assets.

The point estimate of the effect of guaranteed loans on the probability to dissolve is negative and significant in each of the time horizons considered. Marginal effects indicate that treated companies are 2.42 percentage points less likely to be dissolved in the treatment year than matched peers. Figure 6 shows that the marginal effect increases in time in absolute terms: if one considers a four-year period after treatment, treated companies are 4.20 percentage points less likely to dissolve than their peers. In the second year after treatment the point estimate of the treatment effect is -3.35 percentage points and the 99% confidence interval is [-3.93, -2.77].

As the predicted probability of dissolution for untreated firms in the second year after treatment is 5%, the magnitude of the effect is economically important. The number of loans included in the analysis ranges between 14,666 (year of the treatment) and 15,379 (fourth year after treatment). The number of observations in this case does not decrease with T because information on survival is available until 2018 for all companies, and its availability does not depend on the number of years after treatment.

Figure 6: Estimated treatment effect on probability of dissolution



Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on the probability of dissolution from the year of the treatment to the fourth year after treatment. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The figure reports the point estimate of the treatment effect (broken line, on left axis) as well as the lower and upper bounds its 99% confidence interval (shaded region), and the number of loans (vertical bars, on right axis) included in each regression.

Besides being an interesting result per se, the fact that the receipt of guaranteed loans has a positive effect on survival also excludes the possibility that the results illustrated earlier are affected by an upward survivorship bias. If anything, we may have underestimated the treatment effect along the other performance dimensions.

In fact, companies that are dissolved are excluded from the analysis, because of the lack of accounting data. Since control group companies are more likely to dissolve than treated companies, the worst performing companies will drop out more from the control group sample than the treatment sample. Therefore, our estimate of the treatment effect is based on the comparison of treated companies with the "best" (i.e. surviving) companies within the control group. This may have caused a downward bias in the estimate of the treatment effect, which means that what we estimated is possibly a lower bound treatment effect.

3.1.7. Focus on sole proprietorships: a loan default analysis

For reasons of data availability exposed in section 2.1, we are not able to estimate the effects of guaranteed loans for sole proprietorships. To mitigate this information gap, we provide here a short descriptive overview of the degree of riskiness of sole proprietorships supported by EU guarantees. This analysis depends almost exclusively on the administrative data collected by the EIF. An extended version of this section can be found in Bertoni et al. (2018b).

For this exercise, we could only focus on the CIP mandate. This is because, for administrative reasons, the default data pertaining to the MAP mandate were not collected at the loan level, but at the portfolio level. In fact, we could only focus on two countries, related to two different macro-regions: Italy and Belgium. As opposed to the rest of the paper, this section refers specifically to the two countries. At any given point in time, a firm may have defaulted on several loans, or only on a subset of them. When the latter happens, we assume that the firm will/has default/ed on all of its loans. [14] In line with our main analysis, we aggregate loans granted in the same year for each firm.

Data on defaults is received by the EIF on a quarterly basis, the most recent defaults having occurred in the first half of 2018. We also note the *censored* nature of the data, which affects statistics over time. Since more recently disbursed loans come with a shorter time window to observe their potential default, we do measure a lower riskiness, but this may be purely data-induced (see Figure 7).

The distribution of loans and defaults varies by legal form. Sole proprietorships experienced more defaults than limited companies, and limited companies more than partnerships, as shown in Figure 8.

Figure 7: Loan defaults per quarter (all forms)

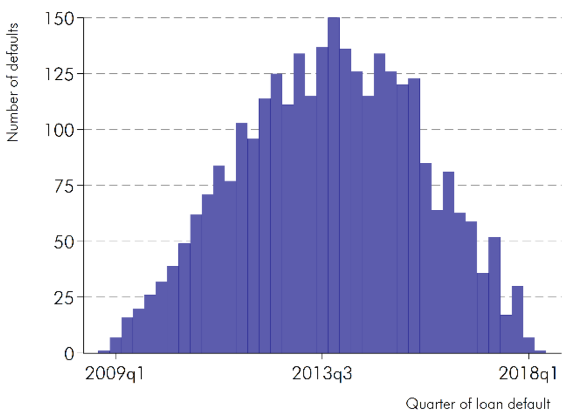
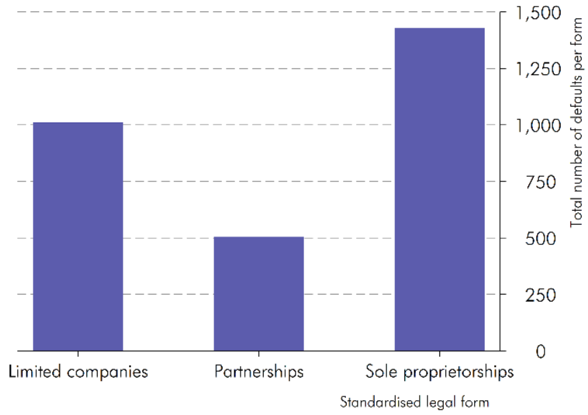


Figure 8: Number of defaulted loans per legal form



At the aggregate level, one would assume that sole proprietorships would default more on their loans, since they would tend to be smaller and/or more fragile firms. However, surprisingly, the

[14] Only in 0.75% of cases we observe firms defaulting on fewer loans that they received, mostly because a default in their latest loans have not yet been recorded.

share of defaulted loans over total loans is higher for limited companies (5.71%), than for sole proprietorships (4.74%) and for partnerships (2.95%). Default rates are much higher for sole proprietorships in Belgium. A mix of different factors likely explains this difference. First, in Table 8, we observe significant differences in sectoral composition between the two countries. Belgian sole proprietorships are highly concentrated in the retail industry (G-I), which makes up for more than half of the sample. In the Italian case, we observe a relative bias towards more traditional sectors, *i.e.* manufacturing and construction, a feature that is likely to affect observed default rates.

Table 8: Sectoral breakdown of sole proprietorships, by country

Country code	A	B-E	C	F,L	G-I	J-N	P-T
Belgium	1.01%	0.13%	6.29%	9.35%	51.57%	11.80%	19.84%
Italy	2.22%	0.25%	17.01%	22.07%	39.79%	5.21%	13.46%

Second, the different industrial systems across countries may have been pivotal in the period under analysis: Belgian recipients could have been more sensitive to the defaults of large firms, whereas Italian recipients, typically organised in dense networks of small businesses, may have been more resilient to default propagation. Different bankruptcy laws and procedures may have also played a role.

Third, the lending strategy of partner financial intermediaries has a crucial role in the loan disbursement mechanism, hence in explaining default rates. Italian intermediaries under CIP are mostly organised in the form of "Confidi". These are two-layer systems, in which the first (local) layer ensures that the system benefits from the specific knowledge of its local members, while the second layer allows for risk sharing across the local CGSs (see Chatzouz et al., 2017). Against this backdrop, loan disbursement to sole proprietorships may have been predominantly driven by pre-existing business relationships, *i.e.* targeting intermediaries' existing network of clients. Conversely, Belgian intermediaries may be aiming at expanding their client base towards new, hence riskier, clients. This is in line with the fact that, also for other legal forms, Belgian beneficiaries tend to be riskier than their Italian counterparts.

In terms of sectors, a few sectors deviate from the aggregate default rate. These exceptions are manufacturing, mining, utilities, information, finance, real estate, "Professional, scientific and technical activities", administrative services, education, human health, arts and entertainment, other services, and household activities. In these sectors, sole proprietorships have higher default rates than limited companies. We infer that the aggregate default rate for sole proprietorships is driven by more traditional sectors such as construction, trade, transportation, and accommodation.

Across firm age classes, defaults tend to decrease with age over all forms, which makes sense considering the higher risk profile of – and reduced risk mitigation options for – young firms. Very young firms of less than two years do not appear to follow the overall pattern of default rates per form. For these firms, sole proprietorships have higher default rates than limited companies and partnerships, proof of their higher vulnerability at a young age. In terms of loan sizes, the analysis is less instructive. The selection mechanism certainly explains the lower default rates for larger loans, particularly for more opaque sole proprietorships.

We consider the effect of the economic cycle on loan defaults distinguishing between the year of signature and the year of default. [15] In terms of signature year, there are significant deviations at the beginning and end of the observed period. In 2007-2009, sole proprietorships have higher default rates than limited firms and partnerships. This could be caused by the unfolding of the economic crisis of 2008, which could have disproportionately affected more fragile sole proprietorships. [16]

In terms of default year, the evolution also seems determined by the unfolding of the economic crisis of 2008. First, sole proprietorships default more until 2013. From 2013, limited firms become again the riskiest of the legal forms, in line with the overall finding. This could be linked to the increased financial resilience to economic adversities, which presumably characterises limited liability firms more than sole proprietorships.

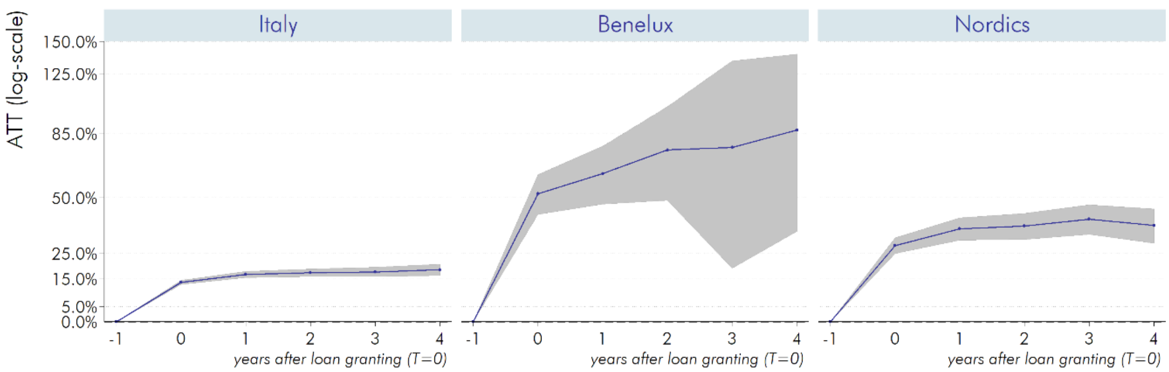
3.2. Results by geographical area

In Figure 9 we illustrate our results on assets, sales and employment cost growth by geographical area. Some interesting differences among the three areas emerge. The first and most obvious difference is in the number of observations included in the analysis. As expected, Italy represents by far the largest geographic area in terms of observations. If we look for instance at estimates on growth in total assets for the second year after treatment, we have 20,213 loans for Italy, 227 for Benelux and 2,056 for the Nordic countries. This implies that once we break down the sample by geographic area, the estimated treatment effects in Benelux and the Nordic countries have much larger confidence intervals than the one for Italy. The number of Benelux companies for which we have sales data is so limited that the models cannot reliably converge for this dependent variable.

In general, the point estimates of the treatment effect are larger in Benelux and the Nordic countries than in Italy. If we look at total assets, the point estimate of the treatment effect for growth in the second year after treatment is 16.7 percentage points for Italy, 61.2 for Benelux and 35.8 for the Nordic countries.

Figure 9: Estimated treatment effect for financial performance indicators by geographic area

Figure 9a: Treatment effect on total assets by geographic area



[15] Default rates by year are computed as the ratio of all defaults in a given year over the number of active (non-defaulted) loans in the same year.
[16] For 2015-2017, the same pattern occurs, but the limited number of observed defaults for firms supported in this period does not constitute conclusive evidence.

Figure 9 continued

Figure 9b: Treatment effect on sales by geographic area

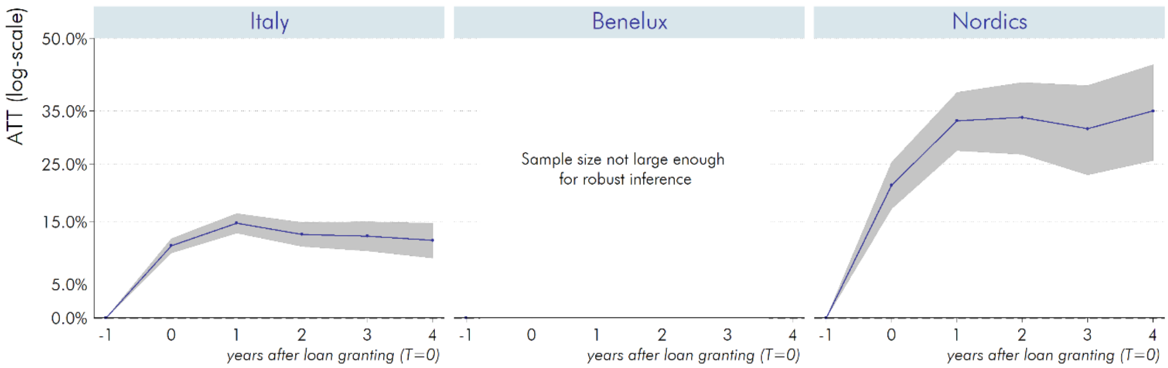


Figure 9c: Treatment effect on employment costs by geographic area

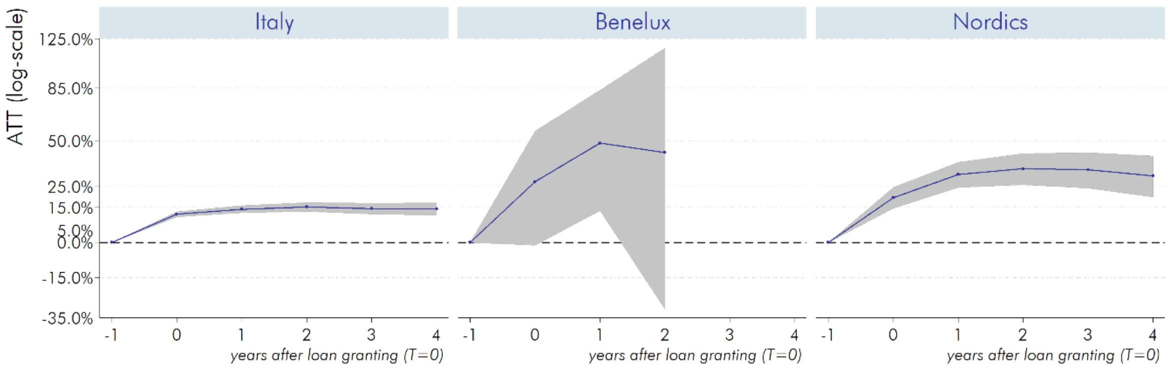


Figure 9d: Treatment effect on profit before taxes by geographic area

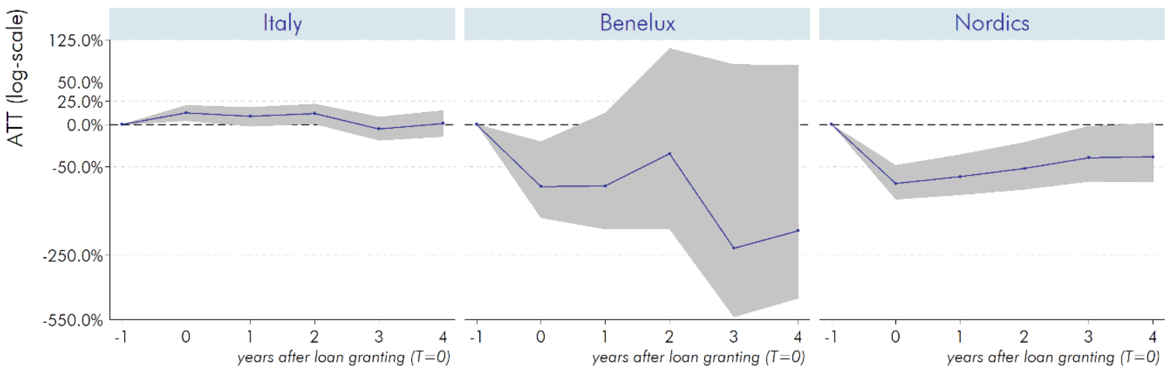
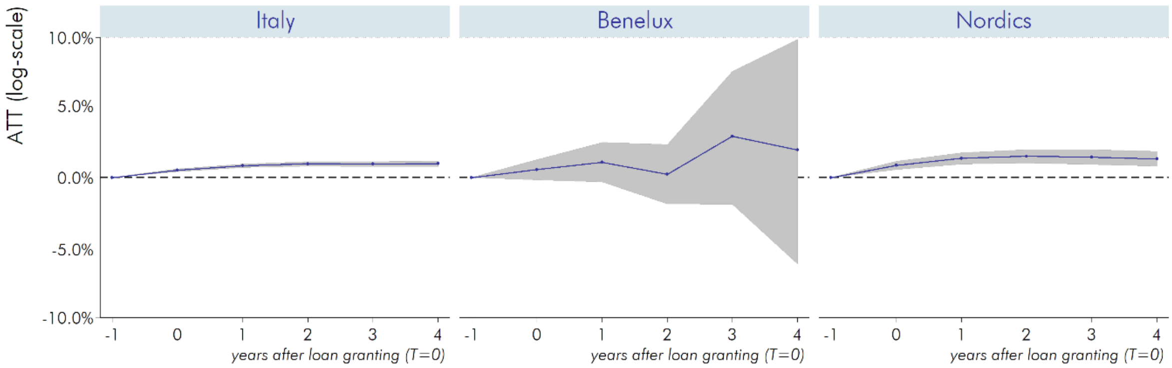


Figure 9 continued

Figure 9e: Treatment effect on assets intangibility by geographic area



Note: the figures summarise the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on total assets, sales, employment costs, profits before taxes, and intangible to total assets, from treatment year to the fourth year after treatment. A log-scale is used due to the different orders of magnitude. The treatment effect is estimated after 1:1 matching (CEM followed by PSM) based on firm's characteristics at time t (beginning of the signature year). The figure reports the point estimate of the treatment effect (blue line) as well as its 99% confidence interval (shaded region.

In terms of survival, we are only able to compare the treatment effect (measured in terms of marginal effects) in Italy and Benelux, because information on bankruptcy and acquisitions is seldom available for firms located in the Nordic countries. We find that the effect of guaranteed loans is much stronger in Benelux than Italy, with a reduction in the likelihood to be dissolved equal to 11.2 percentage points 2 years after treatment, against 3.3 in Italy.

These results on the cross-geographic areas differences in the treatment effect of loan guarantees call for an in-depth analysis to assess whether they are generated by sample composition differences (e.g., industry, size and age) as well as the intensity of the treatment (i.e. amount of the loan). We know from section 2.1 that substantial differences exist across the three geographic areas in the amount of the guaranteed loans, the size of the beneficiaries and their distribution over time and across industries. Specifically, in the year of the loan, Italian companies were bigger, older and more profitable than in other countries, while in Benelux beneficiaries were the youngest. In terms of industry distribution, guaranteed loans in Italy and Nordic countries were more concentrated in manufacturing, while in Benelux trade was the most frequent sector. Loan amounts were smallest in Italy, followed by Nordic countries and Benelux.

In order to take these differences into account, we take Italy as the benchmark scenario and proceed as follows. First, we calculate the "unconditional" difference in the two-year growth in the dependent variable (total assets, sales, employment costs, profits before taxes) between Italian beneficiaries and beneficiaries in each of the other two macro-regions. [17] Then, we estimate the "conditional" difference by controlling for factors that we know may differ across the macro-regions: the amount of the guaranteed loan (scaled by total assets), size of the beneficiary, industry (NACE 2 digits) and signature year. Results are reported in Table 9.

[17] Note that the results in Figure 9 show that long-term effect of guaranteed loans on profits before taxes are not significantly different from zero for the three countries. For a sufficiently long T there are no significant differences between geographic areas.

Table 9: ATT treatment effect in growth across macro-regions

	Benelux vs. Italy		Nordics vs. Italy	
	Average treatment effect	Conditional average treatment effect	Average treatment effect	Conditional average treatment effect
Growth in total assets	0.5372***	0.0101	0.3504***	-0.0193
	(0.0580)	(0.0445)	(0.0389)	(0.0387)
Growth in sales	0.6417***	0.2813†	0.4502***	0.1563**
	(0.1557)	(0.1649)	(0.0503)	(0.0513)
Growth in employment cost	0.5214***	0.1616	0.3933***	0.1205*
	(0.1239)	(0.1112)	(0.0524)	(0.0537)
Growth in profits before taxes	0.7512**	-0.7940***	0.2223	-0.1756
	(0.2463)	(0.2319)	(0.1726)	(0.1726)

Note: the table reports the results of the average treatment effect and conditional average treatment effect (estimated using OLS with robust standard errors) in growth in the third year after treatment in total assets, sales, employment cost and profits before taxes between beneficiaries located in Benelux vs. Italy (first two columns) and in the Nordic countries vs. Italy (latter two columns). When estimating the treatment effect we control for: the amount of the guaranteed loan (scaled by total assets), the size of the beneficiary, industry (NACE 2 digits) and signature year. † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 9 proves that, once we control for differences in the loan amount, size, industry and age at signature year, most of the differences between the growth rate of treated companies in Italy and in the other two macro-regions disappear. Whereas the "unconditional" differences are all positive and highly significant for Benelux vs. Italy (indicating that beneficiaries in Benelux grew more than beneficiaries in Italy in the first three years after the receipt of the loan), such difference is not statistically significant at customary confidence levels (or changes sign altogether) once we control for the abovementioned parameters.

The evidence for Nordic countries vs. Italy is more nuanced, but we may still conclude that the majority of the difference in the treatment effect that we see between Italy and the Nordic countries is due to observable differences in the beneficiaries and in the loan amount rather than in some intrinsic difference between the two geographic areas.

Overall, we can conclude from this analysis that the average treatment effect indeed differs across the three geographical areas under consideration. However, for the most part, this difference is due to how the programme has been administered in the different areas. As we will discuss below, guaranteed loans are more effective on small beneficiaries and when the loan amount is larger. Accordingly, it should not come as a surprise that the treatment effect is larger in the geographical areas in which, on average, beneficiaries were smaller and the loan amount (as a fraction of total assets) was larger.

3.3. Moderating effects

In Table 10, we investigate the treatment effect of the amount of guaranteed loan received by firms. We also examine how the treatment effect of receipt of a guaranteed loan varies by age and size of the recipient firm. We focus on the treatment effect in the second year after the end of the signature year calculated using PSM following CEM, following our baseline approach.

Table 10: Moderation effects of loan amount, age and size

	Total assets	*Sales*	*Emp. cost*	*Profits*	*Int/total assets*	*Dissolution likelihood (marginal effects)*
Moderation effect of loan amount by years after treatment:						
treatment year	0.2989***	0.0935***	0.0553**	-0.1533***	0.0009	-0.0348*
	(0.0104)	(0.0168)	(0.0193)	(0.0409)	(0.0010)	(0.0187)
first year after treatment	0.3849***	0.1887***	0.1302***	-0.019	0.0036**	-.0496***
	(0.0128)	(0.0201)	(0.0288)	(0.0485)	(0.0012)	(0.0152)
second year after treatment	0.4244***	0.2011***	0.1427***	0.1032*	0.0049**	-0.0345***
	(0.0122)	(0.0219)	(0.0293)	(0.0477)	(0.0015)	(0.0127)
third year after treatment	0.4434***	0.1990***	0.1424***	0.0158	0.0047**	-0.0418***
	(0.0161)	(0.0243)	(0.0369)	(0.0576)	(0.0017)	(0.0122)
fourth year after treatment	0.4363***	0.1762***	0.1275**	0.0769	0.0049**	-0.0543***
	(0.0189)	(0.0284)	(0.0423)	(0.0599)	(0.0017)	(0.0132)
Moderation effects coefficients (only second year after treatment):						
Age 5-16 vs. Age<5	-0.0605***	-0.0695***	-0.1169***	0.0187	-0.0031*	-0.0010***
	(-0.0147)	(-0.0194)	(-0.0215)	(-0.0793)	(-0.0015)	(-0.0035)
Age>16 vs. age<5	-0.1344***	-0.1167***	-0.1593***	-0.0083	-0.0081 ***	-0.0131***
	(-0.0145)	(-0.0193)	(-0.0204)	(-0.0894)	(-0.0014)	(-0.0042)
Assets 320-900 EUR k vs. <320 EUR k	-0.2257***	-0.1464***	-0.1683***	0.0951	-0.0042*	0.0003
	(-0.0202)	(-0.0245)	(-0.0308)	(-0.0817)	(-0.002)	(-0.003)
Assets 900-2,400 EUR k vs. < 320 EUR k	-0.2441***	-0.1658***	-0.1765***	0.0932	-0.0085***	0.0009
	(-0.0195)	(-0.024)	(-0.0295)	(-0.0881)	(-0.0019)	(-0.0038)
Assets >2,400 EUR k vs. < 320 EUR k	-0.2940***	-0.2316***	-0.2008***	-0.1394	-0.0101***	0.0136
	(-0.0193)	(-0.0241)	(-0.0291)	(-0.1032)	(-0.0018)	(-0.0067)

Note: The top half of the table reports the results (OLS with robust standard errors) of the moderating effect of loan amount (defined as loan amount/total assets) on logarithmic growth in in total assets, sales, employment cost, profits and intangible to total assets. Only the relevant parameter is shown with each regression, which also includes all control variables in the main analysis. In the last column, we also show the average marginal effects of loan amount estimated after a Probit with robust standard errors on the probability of dissolution. The bottom half of the table shows the results of the moderating effect of Age and Size (OLS with robust standard errors) on growth in second year after treatment in total assets, sales, employment cost, profits and intangible to total assets. Only relevant parameters shown. Regressions also includes all control variables in the main analysis as well as fixed effects for the moderating variable. In the last column, we also show the difference in the average marginal effects of Age and Size estimated after a Probit with robust standard errors on the probability of dissolution in third year after treatment.

Concerning age, our results for total assets, sales, and employment costs are consistent: the treatment effect is larger in younger companies. The size of these differences across age categories is considerable. If we look, for instance, at growth in total assets, the treatment effect is 6.0 percentage points smaller in companies aged 5-16 years than in companies younger than 5 years, and 13.4 percentage points smaller in companies aged 16+ years than in companies younger than 5 years. We observe no difference across age categories in profits growth, which is consistent with the lack of effect in the general sample.

We find that the reduction in the likelihood to be dissolved that can be attributed to the guaranteed loan is smaller for older companies. In other terms, younger companies benefit more from the loan in terms of survival than older companies.

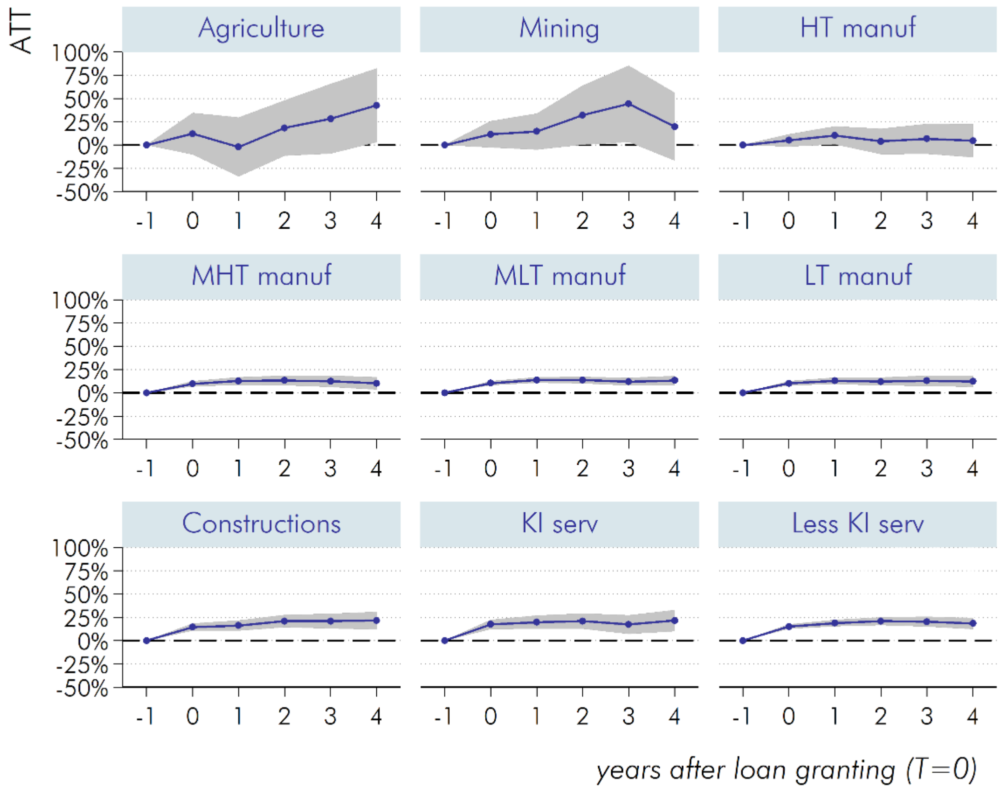
Concerning size, our results relating to the treatment effect on total assets, sales, and employment costs are consistent: the treatment effect is larger in smaller companies. The extent of these differences across size categories is considerable. For instance, for growth in total assets the treatment effect is 22.6 percentage points smaller in companies in the second vs. first quartile, 24.4 percentage points smaller in companies in the third vs. first quartile, and 29.4 percentage points smaller in companies in the fourth vs. fist quartile. We observe no difference across size categories in profits growth, which is consistent with the lack of effect in the general sample. Similarly, regarding survival, we do not find significant differences in the marginal effects of the receipt of the loan on the likelihood to be dissolved in the 3 years after the treatment across size categories. Size does not significantly moderate the extent to which guaranteed loans improve survival.

Consistent with expectations, larger guaranteed loans are associated to a larger treatment effect in terms of total assets, sales, employment costs and intangible assets/total assets growth. The effect is consistent in the four years after the loan and is of large magnitude. We find little evidence of an effect of loan size on profits, except for a negative effect during the treatment year, which is most likely due to the interest paid on the loan itself. This effect disappears in the following years, suggesting that the productive investment made by the company offsets increased interest expenses already from the first year after treatment. For survival, the average marginal effect of the loan amount is negative on the likelihood of being dissolved in all four years after treatment. In other terms, bigger loans reduce the probability of being dissolved more than smaller loans.

Figure 10 explores the moderating role of industries. We focus on our results for employment cost for this analysis, which are representative of other performance indicators. First, we observe that we have very few observations in agriculture and mining. Accordingly, the confidence intervals are generally very large, so there is little we can say about the treatment effect in these sectors. Within manufacturing, we observe similar growth rates across different categories of technological intensity, with the exception of high-tech (HT) manufacturing, where the growth rate is low and not significant (in part because of the limited number of observations). If we look in the second year after treatment at the treatment effect on employment cost growth we find: +4.69 percentage points for HT manufacturing (not statistically significant), +12.85 percentage points for medium-high-tech (MHT) manufacturing (significant), +13.67 percentage points for medium-low-tech (MLT) manufacturing (significant), +12.00 percentage points for low tech (LT) manufacturing (significant). The effect seems to be larger in services than manufacturing but again with little difference across the two categories: if we look at the effects on employment growth in the second year after treatment, we find +21.22 percentage points for knowledge intensive (KI) services (significant) and +21.00 percentage points for less KI services (significant).

The conclusion we may draw from this analysis is that guaranteed loans are typically less effective at boosting growth in the most high-tech manufacturing industries, in which asymmetries of information are supposedly higher and a greater effect should in principle be observed. Specifically designed guarantee instruments, or other equity instruments or equity-like financing (e.g., participative loans) could perhaps show more effective in supporting these high-tech companies.

Figure 10: Estimated treatment effect for employment cost across different industries



Note: the figure summarises the results of the regressions (OLS with robust standard errors) on the estimated treatment effect of guaranteed loans on employment costs from the treatment year to the fourth year after treatment, based on CEM followed by PSM across different industry groups. The figure reports the point estimate of treatment effect (broken line) as well as the lower and upper bounds of the 99% confidence interval (shaded region), and the number of loans (vertical bars) included in each regression.

4 Conclusions

In this paper, we provide reliable estimates of the firm-level economic additionality of EU CIP and MAP guaranteed loans in terms of assets, sales, employment growth, profitability, assets intangibility and chances of survival. To do so, we use a rigorous econometric framework to estimate the "treatment effect" of guaranteed loans. Our counterfactual is based on a combination of coarsened exact matching (Iacus, King, & Porro, 2012), propensity score matching (Rosenbaum & Rubin, 1983) and difference in differences estimation. Our results show that this particular guarantee policy instrument was effective in boosting the growth, increasing intangibility (a proxy for innovation) and the chances of survival of beneficiary firms. We did not detect significant effects on profitability.

In line with the theory that more financially constrained companies are subject to stronger barriers to growth, we find that the treatment effect of guaranteed loans is stronger when the beneficiary is small and/or young, as well as when the size of loan is larger. The effects are larger for firms in services than in manufacturing industries, but do not seem to be larger in high-tech and knowledge-intensive sectors vs. low-tech sectors. We also document the large differences in the magnitude of the economic additionality across the three geographical areas under consideration. The effects in the Nordic countries are more than double in size than those in Italy (which are nevertheless positive), and those in Benelux are almost twice as large as in the Nordic countries. The discrepancies between countries stem from differences in terms of loan sizes, the age and industry of beneficiary firms, and the specific ways the policy instrument was channelled to firms via financial intermediaries.

Combined with Asdrubali and Signore (2015) and Bertoni, Colombo and Quas (2018a), this is the third paper to analyse the economic effects of loan guarantee instruments to European SMEs. While the key findings of all three studies robustly reinforce each other, a comparative analysis of the economic effects in countries served by the MAP and CIP programmes could offer a pan-European perspective on the economic effects of EU loan guarantee schemes. We leave it to a future study to address this important research question.

There are some limits to our results. Aside from the theoretical caveats discussed in section 2.6, our analysis looks exclusively at the firm-level economic benefits of guarantees, without considerations to the implied financial risk and/or cost. These are likely to be higher for younger and smaller firms. We leave it to future research to shed additional light on the potential risk/additionality trade-off of loan guarantee instruments.

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Annexes

Appendix I: Robustness checks

Sample selection

As discussed in section 2.1, only a subset of the population of the loan guarantees beneficiaries can be included in the treatment analysis. For instance, some companies could not be found in Orbis. Some others did not have any accounting data, or did not have relevant accounting data in year t or t+T. This latter category includes companies that were not active before the loan granting year (hence did not have financial statements in t) as well as companies that ceased to exist between t and t+T (hence do not have financial statements in year t+T).

We estimate a probit model in which the dependent variable is equal to one if the beneficiary is included in 3-year growth treatment effect estimation, and the control variables are: the logarithm of firm age, the logarithm of the number of employees at time of signature, and dummy variables for country, signature year, and 2-digit NACE code. The results are reported for three dependent variables (Total assets, Turnover and Employment cost) in Table 11.

Table 11: Sample selection

Panel A: first-stage probit model

	Total Assets	Turnover	Employment cost
Ln(Age)	0.1586***	0.1779***	0.1510***
	(0.0109)	(0.0112)	(0.0108)
Ln(Employees)	0.1473***	0.1532***	0.1778***
	(0.0101)	(0.0103)	(0.0100)
Obs.	24,029	24,029	24,029

Panel B: Loan amount and growth excluding IMR

	Total Assets	Turnover	Employment cost
Ln(Loan amount)	0.1563***	0.1160***	0.1323***
	(0.0073)	(0.0107)	(0.0102)
Initial size	-0.1610***	-0.1628***	-0.1891***
	(0.0091)	(0.0132)	(0.0142)
Ln(Age)	-0.0447***	-0.0535***	-0.0588***
	(0.0067)	(0.0086)	(0.0100)

Panel C: Loan amount and growth including IMR

	Total Assets	Turnover	Employment cost
Ln(Loan amount)	0.1569***	0.1157***	0.1319***
	(0.0073)	(0.0106)	(0.0100)
Initial size	-0.1754***	-0.1818***	-0.2659***
	(0.0102)	(0.0156)	(0.0222)
Ln(Age)	-0.0726***	-0.0911***	-0.1473***
	(0.0084)	(0.0125)	(0.0146)
IMR	-0.4034***	-0.4842***	-1.3810***
	(0.0852)	(0.1249)	(0.2113)

*Note: all regressions include dummy variables for country, signature year and 2-digit NACE code. *** indicates p-value<0.1%.*

As expected the coefficients of age and size (captured by number of employees) are both negative and significant, meaning that companies that are smaller and younger are less likely to be included in the analysis, because they are those for which accounting data are less often available.

Based on this probit model we construct an Inverse Mills Ratio (IMR), which captures the effect of sample selection on the treatment variable along the lines of Heckman (1979). Although the specification and the sample are slightly different, our results in Panel B are consistent with those illustrated in section 3.3: growth is faster for smaller and younger companies, and for beneficiaries that received a larger loan amount.

In Panel C we add to this simple model the IMR calculated from the probit model in Panel A. Two things emerge from this analysis. First, the IMR is negative and significant, meaning that some unobserved characteristics of the beneficiaries that are correlated with growth are also negatively correlated to the likelihood of a beneficiary being included in the sample. In other words, the companies with the fastest growth are more likely to be excluded from the sample. This is consistent with the fact that companies that are smaller and in earlier stages of development are those that are less likely to have accounting data available in Orbis and, at the same time, they are those that are more likely to grow fast. The specification used in Panel A does not completely control for that (which is somewhat unsurprising given the scarcity of information available for the whole population), and the unobserved part of this heterogeneity is captured by the IMR.

The second important result from this analysis is that, if we compare the results in Panel B and Panel C, we observe that the estimate of the loan amount parameter is essentially identical in the two panels, meaning that, even in this simple setting in which we do not use a dif-in-dif counterfactual, the empirical impact of sample selection is negligible. The estimated parameter for ln(Loan Amount) in Panel B are 0.1563 for total assets, 0.1160 for turnover and 0.1323 for employment cost. The same parameter estimates in Panel C (controlling for sample selection) are respectively: 0.1569, 0.1157 and 0.1319, which are empirically indistinguishable from the ones reported above.

Overall, this analysis, which has its own limitations, suggests that even if a sample selection bias that is not offset by dif-in-dif existed, it would be unlikely to have a material effect on our treatment effect estimations.

Non-parallel growth

A general criticism of matching models is that matched companies could be similar to treated companies at the time of treatment, but could be on a different growth path. In this case, the models would attribute to the treatment something that is instead a non-parallel growth between treated and control group companies, regardless of the treatment.

In order to assess the robustness of the results to non-parallel growth we include, in the regressions, a control for growth in the year before the beginning of the signature year. The coefficient estimates are illustrated in column 2 of Table 12, while detailed results are discussed in Bertoni et al. (2018b).

Overall our results hold after we add this additional control. The size of the treatment effect is slightly lower but overall comparable to that in the main regression (the difference in treatment effect is between 1.5 and 2.5 percentage points).

Credit events

Another potential criticism of the analysis performed in this paper is that whereas we capture the impact of a guaranteed loan, we cannot determine if the treatment is different from that of any loan the company could have received. In other words, would these companies have the same performance if they had any loan, rather than the guaranteed loan?

We can calculate the average increase in leverage as the increase in financial debt/total assets between t-1 and t (we winsorise the variable at the 1% level to reduce the impact of outliers). For the sake of comparability, we refer to treated and control group companies used in the estimates of employment growth models at second year after treatment. In the signature year, treated companies have an increase of 6.41% in their leverage, which is consistent with the fact that the guaranteed loan is a genuine additional source of financing for the company rather than a displacement for already existing financing options.

If we look at the general population of non-treated companies, the average increase in leverage is unsurprisingly very close to zero (0.096%). Matching only partially reduces these differences. Matched companies have on average an increase in leverage (1.97%) that is larger than for the general population, but still significantly less than for the treated companies they are matched against.

An alternative way of looking at increases in leverage is to look at "credit events". Following the literature, we define as credit event any year in which a company has an increase in leverage by more than 5% (Meuleman & De Maeseneire, 2012). Unsurprisingly, credit events are more common for treated companies than for the initial stratified sample of controls: we observe that 38.3% of treated companies experience a credit event in the signature year (i.e., 38.3% of guaranteed loans cause an increase by 5% of more in leverage), which compares to only 8.00% in the sample of non-treated companies. Again, matched companies are closer to, but still below, treated companies (credit events are 14.3% in the matched sample).

Hence, the question is whether the observed growth is driven by the occurrence of a credit event or if the guaranteed loan has an observable effect beyond that. To assess the robustness of the results to credit events we include, in the regressions, a control for the change in leverage from t-1 to t. Results are shown in column 3 of Table 12. Note that we do not use this variable for our baseline approach because of its endogenous nature (the leverage increase could be influenced by the treatment itself).

Table 12: Robustness tests: treatment effect controlling for non-parallel growth and credit event

	(1) Base	(2) Non-parallel growth	(3) Credit event
Total assets	20.56%***	18.23%***	16.94%***
Sales	14.46%***	12.64%***	14.03%***
Employment cost	15.83%***	14.29%***	16.09%***
Profits	-3.76%	2.70%	5.31%
Intangible/Total assets	0.98%***	0.94%***	0.89%***

*Note: the table reports the treatment effect (estimated using OLS with robust standard errors) on growth in second year after treatment in total assets, sales, employment cost, profits and intangible to total assets. Only the treatment effect is shown with each regression, which also include all control variables in the main analysis as well as lagged growth (in non-parallel growth estimates) and increase in leverage (in credit event estimates). ***: p-value<1%.*

Detailed results are reported in Bertoni et al. (2018b). Overall, our results hold after we add this additional control. As expected, the additional control variable is positive and significant in all regressions, meaning that an increase in leverage is indeed followed by an acceleration in growth. However, even controlling for that, the estimated effect of the guaranteed loan remains similar to our baseline model.

Extensive growth model for assets

One critique to our growth models for total asset is that the receipt of a guaranteed loan would have a positive effect on total assets growth merely for accounting reasons and even if the loan were not used for productive purposes or were not used at all (in which case current assets would simply increase by the same amount as financial liabilities). A natural question is thus whether the growth we observe in total assets is additional, i.e. if it goes beyond the mere accounting effect of the receipt of the loan.

Our analysis in section 3.1.1, which looks at how logarithmic growth is affected by the receipt of a guaranteed loan captures a "mechanical effect" and a potential "additionality effect". In this section we estimate a simple model which can shed some light on this issue using extensive rather than intensive measures of growth, i.e., measuring growth in EUR (as a function of loan amount in EUR) instead of logarithmic growth as a function of loan amount to total assets.

We take the sample of treated companies and estimate a dif-in-dif model in which the dependent variable is the extensive growth in total assets (i.e., expressed in EUR rather than in log) and the control variables include the extensive amount of the loan (i.e., expressed in EUR terms rather than as % of total assets), the logarithm of firm's age, raw total assets (i.e., expressed in EUR 2010), and a series of fixed effects for country, signature year and 2-digit NACE code. The full results of the analysis are reported in Bertoni et al. (2018b).

The results of this robustness check suggest that the growth in assets we observe is not merely due to an accounting phenomenon, but it is genuine additional growth. This is consistent with the fact that our main analysis also finds positive growth for other outcome variables (e.g., turnover, employment cost and intangible/total assets) that are not affected by this confounding factor.

Appendix II: List of Acronyms

- CGS: Credit Guarantee Scheme
- CIP: Competitiveness and Innovation Framework Programme
- EC: European Commission
- ECA: European Court of Auditors
- EIF: European Investment Fund
- EU: European Union
- MAP: Multi-Annual Programme
- M&A: Mergers and acquisitions
- OLS: Ordinary Least Squares
- PBT: Profit and Loss Before Taxes
- PS: Propensity Score
- PSM: Propensity Score Matching
- ROA: Return-on-Assets
- SME: Small and Medium-sized Enterprise

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