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The long-term effects of loan guarantees on SME performance

Fabio Bertoni, Massimo G. Colombo

SKEMA Business School – Univ. Côte d'Azur

Politecnico di Milano, School of Management Anita Quas, University of Milan

Abstract. We estimate the treatment effect of guaranteed loans on the growth of a large sample of French small and medium-sized enterprises (SMEs). The nature of our sample allows us to estimate the treatment effect up to 10 years after the treatment and to consider several performance measures and moderating factors. Our findings indicate that beneficiaries of guaranteed loans experience significantly higher growth in sales, employment, and total assets than otherwise similar companies. The effects are long lasting, do not entail a slowdown in productivity growth, are mostly driven by organic growth rather than by external acquisitions, and are larger in firms that are typically more financially constrained (young or small). Guaranteed-loan beneficiaries are also more likely to survive than non-beneficiaries. Our results are consistent across different identification strategies (matching, difference-in-differences, instrumental variable estimation) and control group choices.

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1. Introduction

Government-sponsored loan guarantees are widespread in both developed and developing countries (Beck et al., 2008), and have for decades been one of the primary mechanisms for facilitating access to debt financing (Kuo et al., 2011). In recent years, governments worldwide have created new loan schemes (e.g., Brown et al., 2021) and have added hundreds of billions of euros to existing schemes to counter the economic slowdown linked to the COVID-19 pandemic. In many countries, these schemes accounted for more than half of the rescue funds provided (Anderson et al., 2020). The Paycheck Protection Program (PPP), for example, launched only few months after the beginning of the global pandemic, has been one of the largest firm-based fiscal policy programs in US history (Granja et al., 2022b).

Many government-sponsored loan guarantee schemes are targeted at small and medium enterprises (SMEs). The policy rationale is that, despite debt financing being the most common source of external financing for SMEs (Brown and Lee, 2019; SAFE, 2019), these businesses find it more difficult and more expensive to access this source of funds than larger companies (Beck et al., 2008; EIF, 2015). In most economies, the vast majority of companies are SMEs (Ayyagari et al., 2007; Infelise, 2014), but financial constraints can hamper their innovation and growth (Hyytinen and Toivanen, 2005; Lee et al., 2015). It is therefore not surprising that lending gaps for SMEs are a major concern for policymakers around the world (OECD, 2020). Government-sponsored guarantees aim to compensate for SMEs' lack of collateral and creditworthiness, thereby reducing the risk for banks and increasing their willingness to lend (Vogel and Adams, 1997).

The objective of this paper is to provide comprehensive and robust evidence regarding the effectiveness of these schemes by analyzing a large and long panel of guaranteed loans in France. The nature of our data allows us to estimate both the *short* and the *long-term* effects of credit guarantees on a large sample of SMEs, and to examine several performance measures and moderating factors, as well as the origin of growth (organic vs. external). Our results are robust to a series of alternative identification methods, which supports the validity of our causal interpretation.

We focus on SME loans guaranteed by the European Union (EU) through the European Investment Fund (EIF). In these loans, 50% to 75% of the principal potential losses are guaranteed by the EIF. The loans are implemented with selected financial intermediaries. In our study we focus on the "Multiannual Programme for Enterprise and Entrepreneurship" (MAP), which was launched in 2002, and on its successor, the "Competitiveness and Innovation Framework Programme" (CIP), which was launched in 2007. These programs have backed almost €25 billion in loans that have benefited hundreds of thousands of SMEs across Europe.

To perform this study, we accessed information on the population of French SMEs that had received EIF-guaranteed loans under the MAP and CIP programs in the period 2002-2016. We used two Bureau Van Dick databases (Orbis and Diane) to retrieve accounting information on 57,208 guaranteed-loan beneficiaries. We estimated the average treatment effect on the treated (ATT) of the receipt of these guaranteed loans in the 10-year period following the year in which the loan was received by beneficiary SMEs. We examined the impact of the guaranteed loans on beneficiaries' sales, employment, and asset growth, and assessed their effects on firm productivity and survival. As discussed below, we obtained similar results when employing different identification methods.

A number of existing studies have examined the impact of guaranteed loans. We contribute to this literature in several ways. First, the existing studies have devoted little attention to the *timing* and *sustainability* of the effect of guaranteed loans. This is a potentially important gap in the literature because the investments made by beneficiaries could take years to produce any visible benefit. A long time-horizon also allows us to determine whether the effects of guaranteed loans are temporary or whether they persist over time. EIF guaranteed loans have been granted to SMEs since the late 1990s (although our data only start in 2002), which allows us to observe their impact over the long term. We identify how long it takes for the loans to produce their full effect on SME performance, and whether such effects are sustained in the long term.

Second, most previous studies consider a relatively narrow set of indicators when assessing the impact of guaranteed loans on firm performance. This issue, which affects growth studies in general (Shepherd and Wiklund, 2009), is particularly problematic when looking at guaranteed loans, which may produce opposing effects depending on the dimension considered (Uesugi et al., 2010). Guaranteed loans may positively affect recipients in some respects (e.g., asset growth), while being detrimental in others (e.g., productivity or survival). We therefore include several performance measures in our analysis, giving a more comprehensive view of the effects of guaranteed loans than is normally found in other empirical works.

Third, another element that has not received sufficient attention in the literature is the beneficiary's mode of growth. Most studies implicitly assume that the observed growth is organic, but this might not necessarily be the case: beneficiaries could, for instance, use their loan proceeds to acquire other companies, thereby growing externally. Because the unit of analysis is the individual firm, the combination of two firms into the same unit would be recorded as employment growth even if no new jobs were created (Davidsson and Wiklund, 2000). The extent to which the observed growth is organic or external is thus an important concern for policymakers, for whom job creation (and hence organic growth) is a key objective.

Fourth, the impact of guaranteed loans is likely to depend on the recipient's characteristics (Briozzo and Cardone-Riportella, 2016; Brown and Earle, 2017). More specifically, guaranteed loans should be more effective when beneficiaries are more financially constrained. We split our sample into subsamples based on age and size, because younger and smaller SMEs tend to be more financially constrained than older and larger ones. Shedding light on this issue provides useful policy insights into the categories of SMEs that would most benefit from guaranteed loan programs in the future.

Our analysis indicates that after receiving a guaranteed loan, beneficiaries grow more than otherwise similar companies in terms of sales, employees, and total assets, although with different time patterns. These effects remain significant and sizeable 10 years after the receipt of the loan. As discussed in Section 4, we estimate that – over a three-year horizon – it takes €168,000 in guaranteed loans to create one job (which is the same order of magnitude as the amount estimated by Granja et al., (2022b), for the PPP). This corresponds to a taxpayer cost of approximately €6,800 per job created (the average salary in France was between €27,212 and €37,049 over the 2002-2016 period).

Our results are robust across different specifications and identification methods. In our main analysis, we use a combination of coarsened exact matching (CEM) and propensity score matching (PSM) to identify a meaningful counterfactual. The results are confirmed across several variations in the matching algorithm (e.g., using only PSM or only CEM, changing the number of neighbors, or using resampling). Additionally, we run our main models using a difference-in-differences (DID) approach. We estimate a standard two-way fixed effects (TWFE) model and dynamic event-study models (Freyaldenhoven et al., 2019; Sun and Abraham, 2021). We also exploit exogenous variation in the density of credit guarantees across regions and time to estimate instrumental-variable panel regressions in which we control for potential endogeneity and reverse causality. All of these models confirm that guaranteed loans accelerate beneficiaries' growth. Finally, we estimate cross-sectional models in which we restrict our sample to firms that experienced a credit event (defined as a >5% increase in the proportion of liabilities to total assets) and compare guaranteed-loan beneficiaries to non-beneficiaries. This analysis highlights that, of those firms that experience a credit event, guaranteed-loan beneficiaries grow faster in terms of sales and employment, but not in terms of assets, possibly because non-guaranteed loans are more likely to be used for the acquisition of assets that can be used as collateral. Again, results are robust to the use of an instrumental variable approach.

We complement our main results by looking at total factor productivity (TFP). We find no evidence that growth following a guaranteed loan comes at the expense of slower growth in TFP. Our results on factors moderating the effectiveness of guaranteed loans indicates a larger effect on SMEs that are more likely to be financially constrained (i.e., smaller or younger). Additionally, although acquisitions accelerated growth for the firms in our sample, most of the treatment effect we observed was caused by organic growth. Survival analysis indicates that guaranteed loans also have a positive effect on firm survival. The fact that treated companies are less likely to be dissolved during the observation period than control group companies means that our results are not biased upward because of survivorship bias.

The paper is organized as follows. In Section 2, we describe guaranteed loan programs, their rationale, and the literature on their effects. In Section 3, we describe our sample and the methodology used to estimate the effect of loans on beneficiaries' performance. Our results using CEM and PSM are presented in Section 4. Section 5 sets out robustness checks using different methods of identification. Section 6 reports additional evidence on the mode of growth, the moderating effects of age and size, and the effects of guaranteed loans on survival and productivity. Finally, Section 7 concludes.

2. Theoretical framework and literature review

2.1. The rationale behind guaranteed loan programs

SMEs tend to be credit constrained because of the high information asymmetry regarding their quality and the low value of their collateral (Berger and Udell, 1998). Banks usually manage their credit risk by asking for collateral, which they then claim in the case of loan default. This option is not always viable for SMEs, since they tend to hold limited tangible assets. In addition, the fixed costs associated with screening, contracting, and monitoring are disproportionally high for small firms (Binks and Ennew, 1996). For these reasons, banks find lending to SMEs less appealing than lending to otherwise similar large companies. Although SMEs partially compensate for these bank lending constraints by using alternative sources of financing (Casey and O'Toole, 2014), financial constraints result in slower growth and make it harder for SMEs to innovate (Hyytinen and Toivanen, 2005; Lee et al., 2015).

A loan guarantee is an arrangement in which a public institution issues a partial or full guarantee against losses on a loan or a portfolio of loans.[1] Guaranteed loans are a common government support mechanism for SMEs (Beck et al., 2008). Credit guarantees reduce the downside risk for banks, which should translate into a greater willingness to lend, especially to companies that lack other forms of downside protection for lenders, such as collateral (Vogel and Adams, 1997). From a regulatory perspective, under the Basel Framework credit guarantees issued by government entities allow banks to assign the risk weight of the government entity to the protected portion of a loan, rather than the often substantially higher risk weight of the borrower. This reduces the corresponding minimum capital requirements and makes guaranteed loans more efficient for banks.

2.2. Empirical evidence on the effectiveness of guaranteed loans

Because of their broad use worldwide (Beck et al., 2008), a substantial body of literature has studied the effectiveness of guaranteed loans at the firm level. The Small Business Administration (SBA) guaranteed loans, available to SMEs in the US since the mid-1990s, have

[1] We do not discuss private credit guarantees in this paper. Such initiatives mostly take the form of mutual guarantee schemes and are normally funded via membership fees with, or without, additional government support (see, e.g., Cusmano, 2018).

attracted substantial interest. In their large and comprehensive study, Brown and Earle (2017) found a positive relationship between SBA loans and employment growth.[2] More recently, evidence suggests that SBA guarantees are effective in increasing lending supply (Bachas et al., 2021). In Canada, guaranteed loans offered under the Canadian Small Business Loans Act improved access to loans and created jobs in the beneficiary companies (Riding et al., 2007; Riding and Haines, 2001). In Italy, Zecchini and Ventura (2009) found a causal relationship between public guarantees issued through the "Fund for Guarantee to SME" and recipients' higher debt leverage and lower debt costs. Similarly, Cowling (2010) observed that UK companies participating in the "Small Firms Loan Guarantee" scheme were less credit rationed. In Spain, receiving bank credit guaranteed by a mutual-guarantee society was found to result in higher growth in beneficiary firms' assets, sales, and sales-to-assets ratio. Moreover, during recessions, the effects were observed to extend to the growth in employment and the sales-to-employee ratio (Briozzo and Cardone-Riportella, 2016). In their examination of evidence from the French government loan guarantee program "Sofaris", Lelarge et al. (2010) found that beneficiaries systematically raised more external finance, paid lower interest expenses, and enjoyed higher growth rates than other similar firms. However, they were also more likely to adopt risky strategies and, accordingly, filed for bankruptcy more often. Barrot et al. (2021) examined worker-level data and found that recovery loans in France had positive effects on workers' employment and earning trajectories. Ughetto et al. (2017) studied the determinants of the credit spreads charged by UK banks on guaranteed loans, finding that a higher incidence of guaranteed loans over the total amount of outstanding loans translated, on average, into a lower spread for beneficiaries.

Kang and Heshmati (2008) and Oh et al. (2009) examined the Korea Credit Guarantee fund and the Korea Technology Credit Guarantee Fund. They found that the guarantees significantly influenced firms' ability to maintain their size and increase their survival rate, but not to increase their R&D and investment and, hence, their productivity. Uesugi et al. (2010) observed that guaranteed loans under Japan's Special Credit Guarantee Program for Financial Stability increased the availability of loans to beneficiaries. However, when loans were provided by

[2] In the US, guaranteed loans are also used to support the allocation of credit in rural areas, although not specifically to SMEs. Rupasingha et al. (2019) studied the USDA's Rural Development program and found that beneficiaries had a lower risk of failure and grew slightly faster than a control group of businesses.

undercapitalized banks, the increased liquidity lasted only a few years. Moreover, the ex post performance of program participants was worse than for their non-participating counterparts. Wilcox and Yasuda (2019) adopted a complementary perspective, examining the effect of SME guaranteed loan programs on the risk-taking of Japanese banks. They found that guaranteed loans were complements to non-guaranteed loans and that an increase in guaranteed loans was accompanied by an increase in non-guaranteed loans. Kim and Yasuda (2019) also found that beneficiaries of guaranteed loans in Japan tended to face greater financial constraints but had better accounting information quality than non-guaranteed borrowers.

A recent stream in the literature has examined the PPP, which was launched to support firms during the Covid-19 pandemic. Granja et al. (2022b) show that banks played a very important role in the deployment of the program, which initially resulted in funds flowing to regions that were relatively less affected by the pandemic. The study also indicates that the PPP had a relatively small impact on employment creation, with funds mostly being used to constitute precautionary savings. Despite positive short-term evidence (Hubbard and Strain, 2020), the initial boost in employment created by the PPP waned by the end of 2020, and the cost per year of employment retained was as high as 3.5-5.2 times median earnings (Autor et al., 2022). Duchin et al. (2022) show that favoritism was one of the unintended consequences of PPP and that guaranteed loans were more likely to be granted to public companies that had personal ties with banks.

Important lessons can be learned from the existing literature on the impact of guaranteed loans on beneficiaries. First, the design of a guaranteed loan program influences its effectiveness in supporting beneficiary firms. Accordingly, results that hold for one program will not necessarily hold for another. Beck et al. (2010) suggest that the most successful schemes, at least in terms of lower loan defaults, seem to be those that use risk management tools (e.g., securitization) and in which credit decisions are not made by a government agency. Both these conditions are met by the EIF credit guarantees, as discussed in the next section.[3] Caselli et al. (2021) find that the

[3] Gobbi et al. (2020) also raise concerns about temporary loan guarantees, which have been proposed to support SMEs during the COVID-19 crisis. Specifically, the authors argue that temporary loan guarantees provide the banks with an incentive to foreclose existing loans as soon as the guarantees expire.

effectiveness of public guarantee schemes depends on the nature of the intermediary, and banks (the intermediary used by EIF) seem to perform better than mutual guarantee institutions.

Second, in order to comprehensively assess the impact of guaranteed loans, it is important to consider several performance indicators. Guaranteed loans may benefit companies in some performance measures but hamper them in other dimensions (e.g., Uesugi et al., 2010). For instance, guaranteed loans could lead to a substitution between capital and labor, and growth in assets could come at the cost of employment growth. Similarly, growth in inputs (capital and labor) does not automatically imply growth in outputs (sales). For instance, if beneficiaries had unprofitable growth opportunities on average, we would observe a growth in inputs without a proportionate growth in outputs. Therefore, it is also important to investigate the productivity of beneficiaries. Finally, higher observed growth could be the result of risk shifting, and calls for the analysis of survival.

Third, the effect of the loans will likely differ in function of the beneficiaries' characteristics, most obviously the extent of their financial constraints. Because the financial constraints faced by SMEs are the main factor driving the widespread use of guaranteed loans (Honohan, 2010), it is natural to expect these loans to be more effective when granted to firms that are more financially constrained. Somewhat surprisingly, and despite some notable exceptions (e.g. Brown & Earle, 2017), there is relatively little empirical evidence on the heterogeneity of the treatment effect of guaranteed loans across categories of firms with different exposure to financial constraints.

Finally, other under-researched aspects remain to be fully explored by the literature on the impact of loan guarantee schemes. The lack of evidence regarding the timing and evolution of the effects of these schemes on beneficiaries makes it difficult to clarify whether the positive effects are short-lived and vanish in the long term. Similarly, we could question the extent to which beneficiaries' additional growth (in sales, employment, and assets) is organic or external. The economic impact of guaranteed loan schemes would be negligible if they only encouraged SMEs to acquire other firms, rather than pursuing organic growth.

2.3. *EU guaranteed loan programs*

EU guaranteed loan programs provide guarantees to financial intermediaries as part of the EU's strategy to support small businesses (CEC, 2005). Over the years, the EU has created several guaranteed loan programs (Brault and Signore, 2019). In each program, the EIF signs partnership agreements over a predefined period with selected credit institutions in member countries. The credit institutions in turn identify SME lenders who constitute a loan portfolio guaranteed by the EIF. Each loan is guaranteed up to a pre-specified portion of the principal and losses are capped for each loan portfolio.

The first generation of EU guaranteed loans was launched in 1998 with a total of €2.4 billion in guarantees, which were used to support €6.2 billion of loans. The following generations grew larger and larger: the MAP-SMEG (2002-2008) provided guarantees of €4.7 billion, while the CIP-SMEG (2007-2013) offered guarantees of €7.3 billion. The COSME-LGF operated from 2014 to 2020 on a similar scale.

For this study, we obtained from the EIF the list of all beneficiaries of the second and third generation of guaranteed loans (MAP and CIP) in France, one of the largest participants in the scheme. Between 2002 and July 2016,[4] the MAP and CIP guaranteed loan programs granted a total of 170,825 loans in France: 65,042 guaranteed loans were part of the MAP program (2002-2008) and 105,783 were part of the CIP program (2007-2016).

The average amount of French guaranteed loans was €31,914 (median €16,500), with MAP loans being slightly larger than CIP loans (€33,548 and €29,258 on average, respectively). Figure 1 shows the number and total amount of these loans aggregated by year. The MAP loans peaked in both number and total amount in 2007, while the CIP loans were deployed relatively constantly over the period 2009 to 2014, until the program was phased out between 2015 and 2016.

[Insert Figure 1 here]

[4] Note that there is a time lag between the period in which partnership agreements are signed and the period in which loans are granted for each program. This is due, firstly, to the administrative procedures required to start the partnerships and, secondly, to the fact that each agreement lasts for a pre-specified time period, which may extend after the end of the program. For instance, within the MAP-SMEG program, the EIF signed agreements with credit institutions between 2001 and 2006, but the program only really picked up speed in 2003, and loans were still being granted in 2007.

3. Data and method

3.1. The sample of treated companies

We focused on the population of MAP and CIP guaranteed loans granted to companies in France between 2002 and June 2016. Of the total 170,825 guaranteed loans described in the previous section, we eliminated 24,744 loans that were granted to individuals and sole-proprietorships (for which very limited or no secondary data were available), and focused on the remaining 146,081 loans granted to 102,402 companies (some companies received multiple loans). We aggregated information at the firm-year level (for companies receiving more than one guaranteed loan in the same calendar year), obtaining 136,675 firm-year observations, which we consider as the population of interest for our analysis.

We used SIREN codes (the French business identification number) to retrieve accounting information from Bureau van Dijk's Diane and Orbis databases on the population of beneficiaries for the period 2001-2016. Combining Diane and Orbis allowed us to cover a larger sample and a longer period (Orbis data went only back to 2006 when the data was collected), although it introduces potential survivorship bias because Diane does not include dissolved companies. Accounting information was available in the signature year for a sample of 76,621 firm-year observations (56.06% of the population described above), corresponding to 83,481 guaranteed loans (57.15%) and 55,358 beneficiaries (54.06%).

Table 1 shows the distribution of the sample for which the following accounting data were available: the signature year and amount of the loan and the beneficiary's age, industry, and region. The sample and the population have qualitatively similar distributions (in most cases within 1 percentage point), but χ^2 tests reject the null hypothesis that the two distributions are identical. Smaller loans and loans granted in the earliest periods (2003-2004) are underrepresented, while loans granted in later periods (2011-2014) are overrepresented. The youngest (i.e., less than 1 year old) and oldest (i.e., more than 25 years old) beneficiaries, those in the transportation and accommodation industries, and those located in overseas departments (*Départements d'Outre Mer*) are underrepresented, while beneficiaries in the construction and trade industries and operating in central-eastern France are overrepresented in the sample. All of our regressions include controls for age and fixed effects for region, industry, and signature year.

[Insert Table1 here]

We also identified a population of non-treated companies from the Diane and Orbis databases. We extracted a random sample of companies that matched the empirical distribution of the year in which the treated companies were founded. We extracted untreated companies founded before 2006 (375,414 companies) from Diane and untreated companies founded since 2006 (163,892 companies) from Orbis. The rationale of this approach was to match the data collection process used for beneficiaries and to exploit the advantages of the two datasets: Diane's long-time horizon (containing accounting data from as far back as 1995 at the time of extraction) and Orbis' lack of survivorship bias.

3.2. Dependent variables and controls

The dependent variables ($\Delta Y_{\tau+T}$) of the matching models are the logarithmic growth of: sales, employment (measured by the cost of employees), and total assets ($\Delta Sales_{\tau+T}$, $\Delta Employment_{\tau+T}$, $\Delta Assets_{\tau+T}$).

In our main models, presented in Section 4, we are interested in analyzing the dynamic impact of guaranteed loans in the short and long horizon. Therefore, we computed our dependent variables over time horizons of 1 up to 10 years (*T=1…10*).

All variables were obtained from Orbis or Diane for the period 2001-2016 and were winsorized at 5 percent to limit the impact of outliers.

Our key independent variable is a dummy equal to 1 if the focal firm received a guaranteed loan in calendar year τ: $GLoan_\tau$. In all models, we control for the initial level of the relevant variable, Y_τ (which is the level of Y at the beginning of the treatment year), the logarithmic growth of Y in the year before the guaranteed loan ($\Delta Y_{\tau-1}$), the logarithm of age (*Age*), region fixed-effects (NUTS2 – 18 administrative regions), industry fixed-effects (NACE rev. 2 section – 19 industry groups), and year fixed-effects.

Table 2 shows summary statistics and a correlation matrix for the main variables used in our models. We include *Age*, the level and growth of our main performance measures (sales, employment, and assets), and *GLoan*. Although some variables present high correlation, they are never included in the same regressions.

[Insert Table 2 here]

3.3. Matching

In our main models, presented in Section 4, we used matching techniques to estimate the treatment effect of guaranteed loans (other models using different techniques are discussed in Section 5). We compared changes in each outcome variable after the loan with the corresponding change observed in "similar" non-beneficiary companies over the same period. The most critical element of this approach was to select an appropriate control group of companies similar to the beneficiaries.

We used a combination of PSM (Rosenbaum and Rubin, 1983) and CEM (Iacus et al., 2012) to identify a control group of non-treated companies that were "similar" to the treated ones. PSM estimates the treatment effect by comparing treated companies with matched (non-treated) companies that have the same propensity score (i.e., probability of being treated). The method requires the ex post control of the balancing conditions between treated and matched companies: very different underlying characteristics can result in similar propensity scores, and the treated and matched groups could end up including significantly different companies (e.g., in size, age, industry distribution, etc.). Relevant measures of the balancing of the two groups are Rubin's B, which is the absolute standardized difference of the means of the linear index of the propensity score in the treated and matched group, and Rubin's R, which is the ratio of the variances of the propensity score in the two groups. A Rubin's B value below 25 and an R between 0.5 and 2 are generally recommended (Rubin, 2001).

CEM (Iacus et al., 2012) is a method developed to overcome the balancing issues of PSM. Unlike PSM, CEM allows ex ante control of the matched sample balancing because the matching it performs is based directly on matching variables. Moreover, the balancing is not only focused on the mean, but on the entire variable distribution. Continuous variables are transformed into categorical variables (i.e., coarsened), based on intervals identified by the matching algorithm. CEM then identifies the strata of all the combinations of coarsened continuous and categorical variables and eliminates all treated and untreated companies that do not have a common support, i.e., that do not share common characteristics with companies in the other group. The imbalance between the treated and matched groups can be measured by the L1 index, which is the difference between the multidimensional histograms of all pretreatment covariates between the treated and matched groups.

In our main analysis, we used CEM followed by a 1-to-1 nearest neighbor PSM, which combines the benefits of the two matching methods. Iacus et al. (2012) suggest that a PSM based on samples “cropped” using CEM could inherit some of the imbalance-reducing properties of CEM. Intuitively, CEM removes all the treated and non-treated companies whose characteristics are so unique that they would cause an imbalance. As a result, a PSM that is restricted to the “cropped” sample should be better balanced than a simple PSM. Our results indicate that the combination of CEM and PSM does indeed have a Rubin’s R within the limits and a lower Rubin’s B and L1 than either PSM or CEM alone.

Both the CEM and PSM models are based on the following variables: Y_{τ} (the level of Y at the beginning of the treatment year), $\Delta Y_{\tau-1}$ (the logarithmic growth rate of Y in the year before the treatment year), the age, the region (NUTS2 – 18 administrative regions), and the company’s industry (NACE rev. 2 section – 19 industry groups). We matched beneficiaries one year before the treatment with all observations from the sample of control group companies. Note that we include pre-event growth in the matching variables: this is a particularly important variable because, as our results in Section 5 show, treated companies have above-average growth in the years before the treatment (in Section 5, we show that post-event growth significantly and substantially exceeds pre-event growth). We performed separate matching for each growth measure (sales, employment and assets) and time horizon (T=1…10) on companies for which all relevant information was available.[5]

4. Main results

We report the results based on matching in Table 3. Panel A of Table 3 reports the estimated treatment effect of guaranteed loans on sales growth. Because of data availability, the number of treated companies used to estimate the treatment effect falls from nearly 38,000 for the 1-year

[5] Table A1 in the appendix reports statistics on the balancing of the matching three years after the signature year. We replicate all our estimates using several variations in the matching algorithm: using only CEM, using only PSM, changing the number of neighbors or using resampling in PSM, or using simple OLS. All our key results are confirmed.

growth rate to fewer than 2,000 for τ+10.[6] The table shows that the effect of guaranteed loans on sales growth is positive and significant with a p-value<0.001 from $\tau+1$ to $\tau+9$ and a p-value<0.05 for $\tau+10$. The coefficient for the loan variable in $\tau+1$ implies that the effect of the guaranteed loans is equal to 3.67 percentage points of additional growth in sales. The estimated treatment effect is 6.70 percentage points in $\tau+3$ and relatively stable until $\tau+9$. With respect to the control variables, we observe that smaller and younger companies exhibit more rapid sales growth, which is consistent with expectations based on the results of the "Gibrat literature" (Santarelli et al., 2006; Sutton, 1997). The coefficient of $\Delta Sales_{\tau-1}$ is negative for τ+1 but is positive thereafter, suggesting that sales growth shows signs of mean reversion in the short term but is persistent in the long term.

The results for employment growth are shown in Panel B of Table 3. The treatment effect of guaranteed loans on employment growth is positive and significant with a p-value<0.001 from $\tau+1$ to $\tau+10$. The estimated magnitude of the effect is 3.62 percentage points in $\tau+1$, 6.88 percentage points in $\tau+3$, and 7.46 percentage points in $\tau+10$. With respect to control variables, we observe that smaller and younger companies with higher pre-loan growth rates exhibit more rapid employment growth, which is again consistent with the growth literature.

Panel C of Table 3 shows the results for total asset growth. The effect of guaranteed loans on total asset growth is positive and significant with a p-value<0.001 from $\tau+1$ to $\tau+9$ and a p-value<0.05 in $\tau+10$. Compared to the control group, treated companies grew 7.72 percentage points more in $\tau+1$, 8.93 percentage points more in $\tau+3$, and 4.15 percentage points more in $\tau+10$. Again, smaller and younger companies exhibit more rapid total asset growth. The coefficient of $\Delta Assets_{t-1}$ is not significantly different from zero in most models, and is negative and significant for $\tau+1$ and $\tau+2$.

[Insert Table 3 here]

[6] We replicate the analysis on a balanced sample in which only companies observed for the full 10-year period are included. The overall results, which we omit from the paper for the sake of brevity, are consistent with those presented here. The ATT is positive and significant at 10 percent or better across the three dependent variables and all time periods, with few exceptions.

We can estimate the cost per job created by the program as follows. Based on the estimated 3-year growth in employment from Table 3 (6.88%), and the average number of employees of MAP and CIP beneficiaries (2.76, source EIF), we can estimate that the 170,825 guaranteed loans in France created approximately 32,400 jobs. The total amount of guaranteed loans in France over the period was €5.5 billion, which corresponds to €168,000 of guaranteed loans per job created. This amount (equivalent to $205,000 at the average exchange rate of 1.2209 dollar per euro during the period, source: ECB) is of the same order of magnitude as the $175,000 estimated by Granja et al. (2022b) for the PPP.

However, for EIF-guaranteed loans the taxpayer cost is just a fraction of this amount. The EIF only guarantees a portion of the loan amount and only up to a certain cap rate for the whole portfolio of loans. Based on the cap rate and on the guaranteed rates for the different agreements (source: EIF), a conservative estimate of the taxpayer cost is 4.0% of the loan amount, which corresponds to €219 million for all the MAP and CIP loans in France. This implies a taxpayer cost per job created of €6,800, which is substantially lower that the average salary in France during the period (between €27,212 and €37,049, source: OECD).

5. Alternative identification methods

5.1. Difference-in-differences analysis

In this section, we present results based on an alternative identification method that is also used by the literature to assess the impact of guaranteed loans on beneficiary SMEs: difference-in-differences (e.g., Hubbard and Strain, 2020). The identifying assumptions differ between the two models. Matching models are relatively robust to misspecification of the treatment equation, but rely on the correct identification of the counterfactual (Huber et al., 2013). Difference-in-differences models instead use fixed effects to control for observable and unobservable time-invariant firm-level differences and for time-specific effects on the dependent variable, but may be biased in the presence of pre-event trends or heterogenous effects, especially when the treatment is staggered, as in our case (Baker et al., 2022).

We begin by estimating simple two-way fixed effect (TWFE) models on the logarithm of sales, employment, and total assets. The dependent variables are the annual logarithmic growth of sales, employment and total assets, while the key independent variable is a step variable turning from 0 to 1 in the year in which the company received its first guaranteed loan (*GLoan_step*). We control for firm age and firm fixed effects in each regression. The results, shown in Table A2 in the Appendix, confirm that beneficiaries experience significant (p-value<0.001) sales, employment, and asset growth after receiving a guaranteed loan.

Recent work in econometric theory shows that TWFE estimators can be biased when the treatment is staggered (i.e., units are treated at different times). Contrary to the standard 2x2 difference-in-differences (in which all units are all treated at the same time), staggered difference-in-differences regressions introduce a "bad comparisons" problem, which is amplified when treatment effects change over time (which is most likely the case in our setting, as illustrated in the previous section). Sun and Abraham (2021) propose an interaction-weighted estimator that is consistent in the presence of staggered and heterogenous treatment. The results are presented in Figure 2.

[Insert Figure 2 here]

A visual inspection of Figure 2 confirms a significant discontinuity in the sales, employment, and asset growth of companies at the time of the treatment. Results are similar to those discussed in Section 4 in terms of magnitude and timing.

Another important aspect highlighted by Figure 2 is that a pre-event trend seems to be present for sales and, to a lesser extent, for employment. Beneficiaries were already experiencing above-average growth before the treatment with respect to other companies. Pre-event trends should not bias results presented in Section 4 because pre-treatment growth enters the matching procedure, but they might bias the TWFE estimates in Table A2.

A visual inspection of Figure 2 suggests that guaranteed loans accelerate growth beyond this pre-existing trend. To formally test this hypothesis, we used fully-saturated dynamic event-study models on sales, employment, and total assets to estimate the 3-year growth before the treatment ($\Delta_{\tau-3}Y$), the 3-year growth after the treatment ($\Delta_{\tau+3}Y$), and the difference between the two estimates (*Difference*). Results, shown in Table A3, confirm that these differences are positive and significant across all of our measures (with p-value<0.05 or better), confirming that guaranteed loans are associated with a significant acceleration of growth for beneficiaries beyond any pre-existing trend.[7]

5.2. Instrumental variable analysis

Neither matching nor difference-in-differences can control for the endogeneity arising from time-varying unobservable effects. In other words, the observed relationship between guaranteed loans and growth could for instance be explained by unobservable time-variant characteristics (e.g., profitable business opportunities) that determine both the propensity of a firm to seek and obtain a guaranteed loan and its growth.

To support a causal interpretation of our results, we rely on another identification method: the instrumental variable analysis. Starting from the geographical and time distribution of CIP and MAP guaranteed loans, we build two time-varying instrumental variables at the regional (NUTS 2) level that capture the relative occurrence of guaranteed loans: *#GLoans*, which is the number of guaranteed loans (source: EIF) divided by the number of existing companies in the region/year (source: Eurostat); and *GLoans amount*, which is the amount of guaranteed loans (source: EIF) divided by the amount of all loans in the region/year (source: Eurostat). The key mechanism that justifies the theoretical validity of these instruments is that small business loans are predominantly local and depend on the geographical distribution of bank branches (Granja et al., 2022a). A firm based in a region in which EIF-accredited intermediaries are more active is, all other things being equal, more likely to receive a guaranteed loan. This is a source of exogenous variation that does not influence the beneficiary growth (for a similar approach in the context of guaranteed loans, see, e.g., Brown and Earle, 2017; Granja et al., 2022b).

We use these instrumental variables in a two-stage least-squares fixed-effect panel regression for the growth of sales, employment, and total assets, similar to the one described in section 5.1, in which the independent variable is the dummy *GLoans*, equal to 1 every time a company receives a guaranteed loan. We report our estimates in Table 4.

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[7] Results in Table A3 are consistent across several specifications, including the pre-event trend correction proposed by Freyaldenhoven et al. (2019) and the interaction-weighted estimates proposed by Sun and Abraham (2021). The estimated difference between pre- and post-event estimated growth ranges between 1.37 and 2.37 percentage points for sales, between 4.42 and 6.54 percentage points for employment and between 7.9 and 9.0 percentage points for assets.

[Insert Table 4 here]

For each dependent variable, we report the results of the first-stage regression as well as those of the second-stage IV-regression. In all regressions the two instruments have the expected positive sign and are significant at the 0.1 percent level. We further test the relevance of the instruments using the Kleibergen-Paap under-identification and the Cragg-Donald weak identification test. The Kleibergen-Paap rk statistics, which under the null hypothesis that the model is under-identified (i.e., the instruments are not relevant) have a $\chi^2(2)$ distribution, range between 709.881 and 744.518 (p-value<0.001) for our models. The Cragg-Donald weak identification tests, which test whether the instruments are only weakly correlated with the endogenous regressor, in which case the IV regression may perform poorly, are in the range between 367.099 and 416.252, comfortably above the critical values tabulated by Stock and Yogo (2005) of 19.93. We test the exogeneity of the instruments using the Hansen J-statistic. The null hypothesis of the test is that the instruments are uncorrelated with the error term and are correctly excluded from the estimated equation. The tests, which under the null hypothesis have a $\chi^2(1)$ distribution, do not reject the null hypothesis that the instruments are valid for sales (1.116, corresponding to a p-value of 0.291) and employment (0.268, corresponding to a p-value of 0.605). However, the null hypothesis is rejected at the 5 percent significance level for the regression on asset growth (5.196 corresponding to a p-value of 0.023), which should thus be considered with some care. The coefficient of the instrumented endogenous variable is positive and significant for each dependent variable (p-value<0.001 for sales and employment and p-value<0.05 for total assets).

5.3. Credit-event analysis

In this section, we present an additional robustness test that uses a different approach to identify the control group. Guaranteed loans are designed to be granted to beneficiaries that would not normally qualify for regular, non-guaranteed loans. Guaranteed-loan beneficiaries should therefore be more credit constrained than companies that receive non-guaranteed loans. As a result, we should observe faster growth in guaranteed-loan beneficiaries than in beneficiaries of non-guaranteed loans.

Unfortunately, although we have the complete list of EIF guaranteed-loan beneficiaries, we do not have access to bank records allowing us to identify companies that received regular loans during the periods in question. We therefore need to identify the beneficiaries of regular loans indirectly. We identify companies as having a "credit event" when leverage ((total liabilities-shareholders equity)/total assets) increases by more than 5 percentage points year-on-year (for a similar approach see Meuleman and De Maeseneire, 2012; Vanacker and Manigart, 2010).[8] We can calculate the year-on-year increase of leverage for 4,021,726 firm-year observations, including 49,720 observations corresponding to a year in which a firm receives a guaranteed loan. Credit events represent 1,426,868 observations in the overall sample, including 25,749 guaranteed loans.[9]

We calculate the growth rate for sales, employment, and assets in the three years after a credit event and, in Table 5, we compare this growth rate for beneficiaries of guaranteed loans and for non-beneficiaries. We present OLS results in Panel A and 2SLS results (using the same instruments as in the previous section) in Panel B.

[Insert Table 5 here]

The results for total assets are not conclusive. OLS estimates indicate that total assets grow less for guaranteed-loan beneficiaries than for other companies experiencing credit events, but the estimated coefficient in the 2SLS regression is positive and not significant. However, the results for sales and employment are consistent and show that among companies experiencing a credit event, those that received a guaranteed loan grow significantly more (p-value<0.001 in OLS regressions and p-value<0.05 in 2SLS regressions).

6. Additional evidence

In this section we provide additional evidence on the productivity of guaranteed-loan beneficiaries, on their mode of growth (organic vs external), on the moderating effects of their age and size, and on their survival.

[8] We replicate the analysis using 7.5 percent and 10.0 percent as alternative thresholds: results are qualitatively unchanged.

[9] Within firms experiencing a credit event, Liabilities/Total assets increases by a similar amount for beneficiaries and non-beneficiaries. The mean (median) increase in Liabilities/Total assets for all firms experiencing a credit event is 0.2602 (0.1786) and is 0.2771 (0.2008) for guaranteed loan beneficiaries.

6.1. Productivity

In this section we examine whether the size growth experienced by guaranteed-loan beneficiaries comes at the cost of slower productivity growth or whether, on the contrary, guaranteed-loan beneficiaries grow faster both in terms of size and productivity. We calculate total factor productivity (TFP) using the Levinsohn and Petrin (2003) procedure, separately for each NUTS2 2-digit sector. We then replicate the analyses conducted in the previous section on TFP growth. The results are reported in Table 6. For the sake of conciseness, we only report the results of the analysis for $\Delta Y_{\tau+3}$ (i.e., three years after the guaranteed loan was received), which – based on the results shown previously – is a time period with a sufficiently large number of observations and for which the sign and magnitude of the long-term treatment effect is already visible. Specifically, Column 1 presents the results obtained with the matching method (CEM followed by PSM) used for our main analysis in Section 4 (see Table 3). Columns 2 and 3 illustrate the results of the credit event analysis presented in Section 5.3 (see Table 5). Column 4 shows the 2 SLS IV panel regressions on TFP growth introduced in Section 5.2 (see Table 4).

[Insert Table 6 here]

The results from Table 6 are somewhat inconclusive. We do not find any indication of a lower TFP growth for beneficiaries than for other companies. Instead, although some of the specifications suggest TFP growth is accelerated for guaranteed-loan beneficiaries, neither the cross-sectional nor the panel IV regressions can reject the null hypothesis that TFP growth is not different between beneficiaries and other companies. We can potentially interpret this difference between the results of the IV regressions and of the other methods as an indication that guaranteed-loan beneficiaries experience a productivity shock not caused by the guaranteed loan itself. If this interpretation is correct, guaranteed loans are not the determinants of productivity shocks, but companies that experience productivity shocks are more likely to obtain them. Guaranteed loans may then serve a positive role allocating capital towards firms that have become more productive but that, because of their size, are underserved by credit institutions.

6.2. Organic vs. external growth

In this section, we study the extent to which the growth pattern observed after receiving the guaranteed loan is organic or external. Again, we only report the results of the cross-sectional regressions, focusing on the effects three years after the guaranteed loan was received.

We retrieved the number of acquisitions undertaken by our sample companies from the Zephyr database (Bureau Van Dijk). Acquisitions are rare events: in our sample, only 2,398 companies made one or more acquisitions during the sample period, with the percentage of acquirers being similar in the treated and control-group samples. Our models include the cumulative number of acquisitions carried out by a firm in the 3-year observation period from τ to $\tau+3$ (*Acquisitions*). The results of our matching approach, reported in Table 7, suggest that firms that undertake acquisitions experience faster employment and asset growth than firms that do not. The estimated effect of guaranteed loans is essentially unaffected by controlling for acquisitions (i.e., the coefficients of *GLoan* are virtually unaltered with respect to the main analysis shown in Table 3).[10] Although external growth is an effective strategy for the firms in our sample to accelerate their growth, most of the treatment effect of *GLoan* on growth we observe is due to organic growth.

[Insert

Table 7 here]

6.3. Moderating effects of age and size

In this section, we analyze whether the treatment effect of guaranteed loans on SME performance is larger for SMEs that are more likely to be financially constrained. Again, we focus on $\Delta Y_{\tau+3}$. In particular, we examine whether and how SMEs' size and age, which are generally considered as negatively associated with the extent of financial constraints, moderate the effect of guaranteed loans on growth. To this end, we generated the dummies $Young_{\tau}$, which identifies young companies (i.e., those with below median age at time τ), and $Small_{\tau}$, which

[10] We also examined whether receiving a guaranteed loan increased SMEs' propensity to engage in acquisitions. To this end, we regressed *Acquisition* over *GLoan*, while controlling for firm age, size (sales) and growth (of sales), TFP, TFP growth, and industry, region, and time dummies. The coefficient of *GLoan* was not significant at conventional confidence levels.

identifies small companies (i.e., those with below median sales at time τ). In Table 8, we test whether the 3-year treatment effect is moderated by firm age (Columns 1, 2 and 3) and firm size (Columns 4, 5 and 6) by including these characteristics ($Young_\tau$ and $Small_\tau$) in the models and examining their interactions with $GLoan_\tau$.

Guaranteed loans have a greater effect on young companies as regards employment growth (+1.93 percentage points, p-value<0.01) and asset growth (+1.76 percentage points, p-value<0.05). The effect on sales growth is also greater for young companies, but the difference is smaller in magnitude and not significant. In other words, our results indicate that guaranteed loans help younger companies grow even faster than older companies with no loan (with the partial exception of sales growth).

Guaranteed loans have a larger effect on smaller companies as regards sales growth (+3.18 percentage points, p-value<0.001), employment growth (+4.35 percentage points, p-value<0.001), and asset growth (+5.88 percentage points, p-value<0.001). Smaller SMEs thus benefit more from guaranteed loans than larger SMEs.

To summarize, guaranteed loans are generally more beneficial for younger and smaller SMEs, which are the most likely to suffer from financial constraints that limit their growth.

[Insert Table 8 here]

6.4. Survival

In this section, we study whether companies that received guaranteed loans are ultimately more or less likely to be dissolved because of bankruptcy or acquisition by another firm. The aim of this analysis is twofold. First, while we found that receiving a guaranteed loan has a positive effect on firm performance, we may still find that treated companies are more likely to dissolve because their leverage increases (Cathcart et al., 2020) or because their projects become more risky (Lelarge et al., 2010). The survival rate of beneficiaries is therefore a key element in understanding the impact of guaranteed loans.

Second, we also aim to investigate whether the analysis of firm performance presented earlier is affected by survivorship bias. Because performance and survival are generally positively correlated (firms that are dissolved are often those with poor performance), survivorship bias could lead to the effect of guaranteed loans being overestimated if loan recipients are also the least likely to survive.

To test the effect of guaranteed loans on survival, we adopted a similar approach to that of the main analysis on firm performance. We retrieved information on firms' survival from the Orbis database (dissolved companies are removed from the Diane database 18 months after bankruptcy or acquisition). Orbis has the advantage of maintaining information on dissolved companies, but unfortunately, at the time of the data extraction, it only provided accounting data from 2006 onwards. We were therefore only able to perform survival analysis on companies treated for the first time after 2006. For each company, we randomly extracted non-treated companies stratified over their foundation years from Orbis. We matched each treated firm with a non-treated firm using CEM and PSM (along the lines discussed in Section 3.3). Our CEM variables include year, age, region (NUTS2), and industry (NACE rev. 2 section). The PSM includes additional variables that are usually considered in survival models: sales (in logarithms), the current ratio (i.e., the ratio of current assets to current liabilities), ROA (the ratio of earnings before taxes to total assets), and the solvency ratio (the ratio of shareholder funds to total assets).

The dependent variable is a dummy indicating whether the companies were dissolved between the matching year and 2016. In addition to *GLoan*, we inserted the following controls into the model specification: sales, age, current ratio, ROA, solvency ratio, and year, region, and industry fixed effects.

Our results, shown in Table A4 in Appendix, indicate that *GLoan* has a negative and significant coefficient, with p-value<0.001, even when we control for firm sales, ROA, solvency ratio, and age. Marginal effects indicate that treated companies were about 6.25 percentage points less likely to be dissolved during the observation period than control group companies. Because our results indicate that treated companies are more likely to survive than non-treated companies, we can conclude that the results presented in earlier sections are not affected by an upward bias. Our results can therefore be considered as lower-bound estimates of the effect of guaranteed loans on growth.

7. Discussion and conclusion

This paper contributes to a growing stream of literature focused on investigating the impact of loan guarantee schemes on firm performance, with a particular emphasis on SMEs. We estimated the "treatment effect" on French SMEs of the loans guaranteed by the EC under the MAP and CIP programs managed by the EIF. Our findings show that guaranteed loans have a positive, sizable, and statistically significant "treatment effect" on sales, employment, and assets. This positive effect is confirmed across different identification strategies (matching, difference-in-differences, instrumental variable regression) and control group choices. Our study is original in several respects.

First, we consider a comprehensive set of indicators of firm performance including growth (in sales, employment, and assets), TFP and survival. Contrary to the arguments presented in some previous studies (e.g., Lelarge et al., 2010; Uesugi et al., 2010), we can therefore conclude that the positive effect of guaranteed loans on one performance dimension (e.g., growth in total assets) does not come at the cost of negative effects on other dimensions (e.g., employment and productivity growth, and firm survival). Indeed, compared to non-beneficiaries, beneficiaries are found to grow more rapidly in terms of both outputs (sales) and inputs (employees and assets), do not have lower productivity (TFP) growth and are also more likely to survive than non-beneficiaries.

Second, we estimate the treatment effect of guaranteed loans on firm performance over a long time-horizon (i.e., 10 years). In all our growth models, differences in growth between beneficiaries and non-beneficiaries remain observable 10 years after the guaranteed loans were granted. This makes us confident that that the positive effect of guaranteed loans persists in the long term and is not mean reverting. However, we also show that it may be several years before the full extent of this effect can be observed. The time lag is shorter for asset growth (the treatment effect peaks in τ+2) and longer for sales and employee growth (they peak in τ+3).

Third, previous studies do not distinguish between organic and external (acquisitive) growth. As emphasized by the "mode of growth" literature (McKelvie and Wiklund, 2010), this distinction is important. Growth through acquisitions is generally more rapid than organic growth, especially as regards sales and asset growth. However, the positive effects on growth for the acquiring firms do not necessarily lead to positive effects at a more aggregate level (e.g., the territory where the acquiring and acquired firms are located, see e.g., Lee, 2018), as research on post-acquisition workforce adjustments have long recognized (e.g., Conyon et al., 2002). We find that the positive effects of guaranteed loans on assets, employment, and sales growth that we detect are *not* explained by external growth. Our results are almost unchanged, in magnitude and significance, once we control for SME acquisition activity. This evidence should reassure policymakers about the economic impact of these schemes on aggregate growth and competitiveness.

Fourth, previous works have highlighted that the positive effects of guaranteed loans are not uniform and instead vary across beneficiary firms (Briozzo and Cardone-Riportella, 2016; Brown and Earle, 2017). We add to this literature by showing that guaranteed loans have stronger positive effects (limited to employment and asset growth) on the growth of younger and smaller SMEs, which are more likely to be financially constrained than their more mature and larger counterparts. This is again good news for policymakers attempting to alleviate the financial constraints faced by SMEs.

Our work has limitations that might be resolved by future research in this area. First, although we consider two important firm-level moderators (firm age and size) of the treatment effect of guaranteed loans on SME performance, this effect may be influenced by other factors. In particular, we focus on a specific country (i.e., France). It was therefore not possible to examine how institutional factors that differ across countries (e.g., the rule of law, efficiency of the banking system) modify the treatment effect of guaranteed loans. Second, although we included a large set of performance indicators in our analysis, there are other important dimensions of firm performance, such as technological and managerial innovation, that we did not consider because of a lack of data. Third, non-disclosure agreements prevented us from accessing the details of the partnership agreements between the EIF and financial intermediaries. Examining how differences in these agreements translate into differences in the selection and treatment of beneficiaries would be extremely interesting for both academics and practitioners. Finally, our work only examined the effect of guaranteed loans on firms and excluded individuals and sole proprietorships for which data are scarce or non-existent (at least in France). Access to data at the individual level (e.g., tax declarations) would allow researchers to look at this specific population of beneficiaries, which is largely unexplored in the academic literature.

In spite of these limitations, the findings of our work, which reveal the positive and sizable treatment effect of EIF guaranteed loans on SME performance, send a reassuring message to policymakers who, during the COVID-19 pandemic as in other periods of crisis, have relied extensively on these schemes to alleviate firms' financial constraints and foster growth.

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Figures and Tables

Figure 1: MAP and CIP guaranteed loans – number (column) and total amount (line) by year

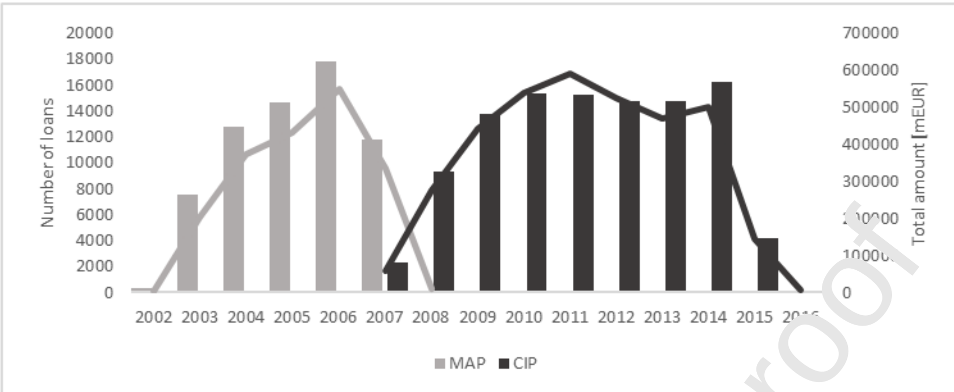
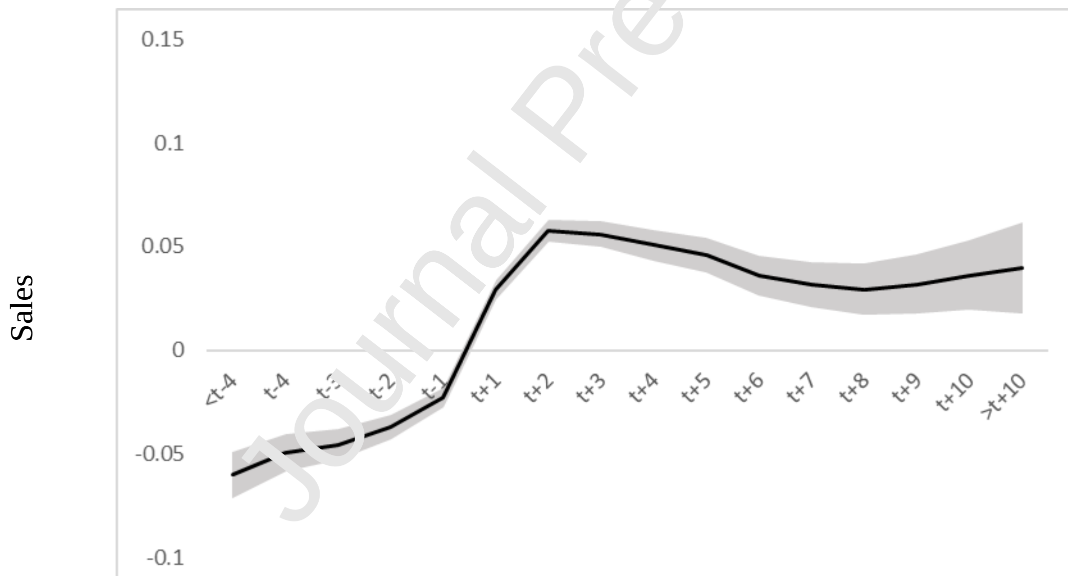
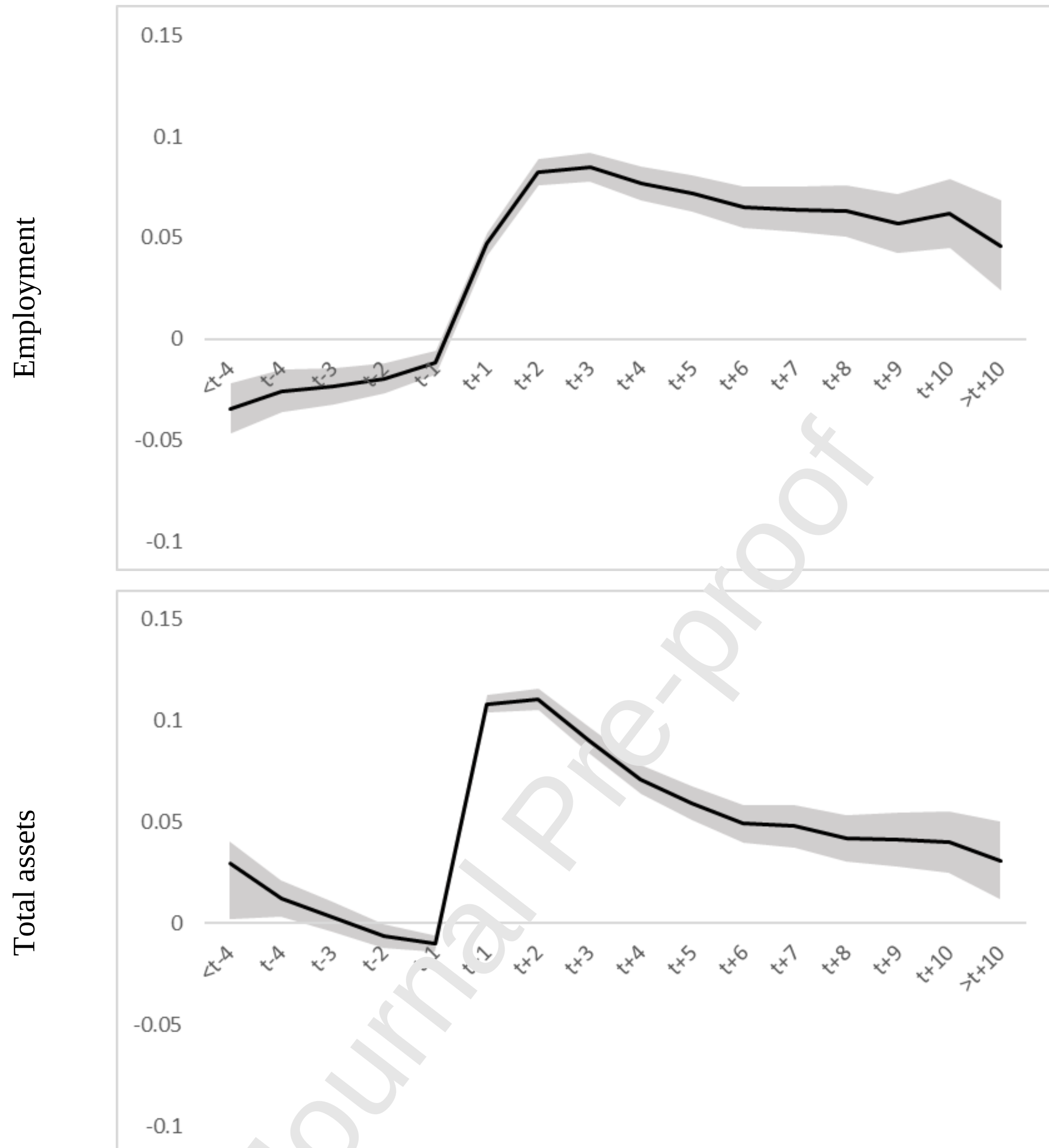


Figure 2: Dynamic treatment-effect estimates





The figure represents the point parameter (solid line) and 95% confidence interval (greyed area) of a fixed-effect panel regression using the interaction-weighted estimator proposed by Sun and Abraham (2021). The dependent variables, reported on the vertical axes, are the natural logarithms of sales, employment, and total assets. The horizontal axis reports the time indicates the years since the receipt of the first guaranteed loan. Control units are non-beneficiaries. The regression includes firm age and firm and year fixed effects.

Table 1: Distribution of the sample of guaranteed loans

	Population		Sample		
	N	Col %	N	Col %	Row %
Panel A: Guaranteed-loan characteristics					
Distribution by signature year					
2003-2004	9,889	7.24	4,687	6.12	47.40
2005-2006	21,051	15.40	10,867	14.18	51.62
2007-2008	17,897	13.09	9,718	12.68	54.30
2009-2010	27,041	19.78	15,164	19.79	56.08
2011-2012	27,880	20.40	17,074	22.28	61.24
2013-2014	28,847	21.11	16,889	22.04	58.55
2015-2016	4,070	2.98	2,222	2.90	54.59
Total	*136,675*	100.00	*76,621*	100.00	56.06
Distribution by guaranteed-loan amount					
Less than €5,000	5,338	3.91	2,267	2.96	42.47
€5,000-9,999	19,837	14.51	9,800	12.79	49.40
€10,000-19,999	43,754	32.01	23,894	31.18	54.61
€20,000-49,999	42,682	31.23	25,904	33.81	60.69
€50,000 and more	25,064	18.34	14,756	19.26	58.87
Total	136,675	100.00	76,621	100.00	56.06

Table 1: Distribution of the sample of guaranteed loans – comparison with the usable population (continued)

	Population		Sample		
	N	Col %	N	Col %	
Panel B: Beneficiary characteristics					
Distribution by age classes					
Less than 1 year old	21,801	16.03	11,190	14.68	51.33
1-5 years old	42,038	30.91	25,247	33.12	60.06
6-25 years old	62,257	45.78	35,479	46.54	56.99
More than 25 years old	9,905	7.28	4,314	5.66	43.55
Total	136,001	100.00	76,230	100.00	56.05
Distribution by industry (NACE Rev. 2 codes)					
Manufacturing (C)	33,140	24.25	19,021	24.83	57.40
Construction (F)	18,355	13.43	11,145	14.55	60.72
Trade (G)	26,115	19.11	16,163	21.10	61.89
Transportation and Accommodation (H-I)	19,466	14.24	8,822	11.52	45.32
Other services (J-S)	30,563	22.36	16,816	21.95	55.02
Other sectors	9,024	6.60	4,646	6.06	51.48

Total	136,663	100.00	76,613	100.00	56.06
Distribution by region					
FR1 (Île de France)	23,363	17.09	13,517	17.64	57.86
FR2 (Bassin Parisien)	19,857	14.53	9,697	12.66	48.83
FR3 (Nord-Pas-de-Calais)	3,587	2.62	2,087	2.72	58.18
FR4 and FR5 (East and West)	32,652	23.89	18,959	24.74	58.06
FR6 (South-West)	20,642	15.10	11,743	15.33	56.89
FR7 (Center-East)	21,082	15.43	12,723	16.61	60.35
FR8 (Mediterranean, including Corsica)	12,905	9.44	7,226	9.43	55.99
FR9 (*Départements d'outre-mer*)	2,584	1.89	667	0.87	25.81
Other	136,672	100.00	76,619	100.00	56.06

Table 2: Summary statistics and correlation matrix

	Variable	Obs.	Mean	Median	Std. dev	1	2	3	4	5	6	7
1	GLoan	6,862,359	0.009	0.000	0.097	1						
2	Age	6,404,941	1.974	2.079	0.[illegible]51	-0.007	1					
3	Sales	4,711,850	6.177	5.984	1.667	-0.020	0.354	1				
4	Δ_{t-1}Sales	3,952,081	0.059	0.032	0.244	0.011	-0.243	0.073	1			
5	Emp	4,585,139	4.723	4.652	1.[illegible]29	-0.020	0.339	0.856	0.022	1		
6	Δ_{t-1}Emp	3,816,685	0.073	0.041	0.266	0.009	-0.257	0.008	0.596	0.051	1	
7	Assets	4,779,170	5.754	5.545	1.716	-0.034	0.354	0.837	0.021	0.774	-0.014	1
8	Δ_{t-1}Assets	4,021,589	0.051	0.020	0.235	0.009	-0.142	0.054	0.464	0.026	0.289	0.094

The table reports summary statistics and pairwise correlations for the main variables used in our analysis. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. *Age* is the logarithm of firm age. *Sales* is the logarithm of firm sales. Δ_{t-1}*Sales* is the logarithmic annual sales growth. *Emp* is the logarithm of firm employment. Δ_{t-1}*Emp* is the logarithmic annual employment growth. *Assets* is the logarithm of firm assets. Δ_{t-1}*Assets* is the logarithmic annual asset growth. Pairwise correlations are based on 3,664,958 observations.

Table 3: Beneficiaries' growth after receipt of guaranteed loan

Panel A: Sales

	$\Delta_{\tau+1}$Sales	$\Delta_{\tau+2}$Sales	$\Delta_{\tau+3}$Sales	$\Delta_{\tau+4}$Sales	$\Delta_{\tau+5}$Sales	$\Delta_{\tau+6}$Sales	$\Delta_{\tau+7}$Sales	$\Delta_{\tau+8}$Sales	$\Delta_{\tau+9}$Sales	$\Delta_{\tau+10}$Sales

GLoan	0.0367***	0.0610***	0.0670***	0.0625***	0.0656***	0.0589***	0.0522***	0.0609***	0.0603***	0.0372*
	(0.0014)	(0.0021)	(0.0028)	(0.0036)	(0.0045)	(0.0056)	(0.0070)	(0.0090)	(0.0119)	(0.0183)
$Sales_{\tau-1}$	-0.0128***	-0.0207***	-0.0219***	-0.0267***	-0.0299***	-0.0298***	-0.0289***	-0.0244***	-0.0137	-0.0177
	(0.0010)	(0.0015)	(0.0020)	(0.0026)	(0.0033)	(0.0041)	(0.0052)	(0.0066)	(0.0088)	(0.0140)
$\Delta_{\tau-1}$Sales	-0.0134*	0.0130†	0.0500***	0.0592***	0.0899***	0.1326***	0.1382***	0.1310***	0.1971***	0.3592***
	(0.0053)	(0.0076)	(0.0101)	(0.0127)	(0.0164)	(0.0204)	(0.02[illegible]1)	(0.0334)	(0.0448)	(0.0702)
Age	-0.0377***	-0.0600***	-0.0714***	-0.0834***	-0.0923***	-0.0975***	-0.1003***	-0.1175***	-0.1219***	-0.1252***
	(0.0010)	(0.0015)	(0.0020)	(0.0026)	(0.0033)	(0.0041)	(0.0051)	(0.0067)	(0.0089)	(0.0135)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	75,876	65,518	53,682	43,246	33,800	25,570	18,614	12,874	7,984	3,724
Loans	37,938	32,759	26,841	21,623	16,900	12,785	9,307	6,437	3,992	1,862
R2	0.058	0.08	0.081	0.076	0.072	0.071	0.068	0.069	0.074	0.087

Panel B: Employment

	$\Delta_{\tau+1}$Emp	$\Delta_{\tau+2}$Emp	$\Delta_{\tau+3}$Emp	$\Delta_{\tau+4}$Emp	$\Delta_{\tau+5}$Emp	$\Delta_{\tau+6}$Emp	$\Delta_{\tau+7}$Emp	$\Delta_{\tau+8}$Emp	$\Delta_{\tau+9}$Emp	$\Delta_{\tau+10}$Emp
GLoan	0.0362***	0.0635***	0.0688***	0.0739***	0.0698***	0.0689***	0.0677***	0.0737***	0.0624***	0.0746***
	(0.0016)	(0.0023)	(0.0031)	(0.0039)	(0.0048)	(0.0059)	(0.0074)	(0.0091)	(0.0122)	(0.0178)
$Emp_{\tau-1}$	-0.0298***	-0.0473***	-0.0591***	-0.0594***	-0.0686***	-0.0618***	-0.0720***	-0.0627***	-0.0790***	-0.0724***
	(0.0012)	(0.0018)	(0.0024)	(0.0030)	(0.0036)	(0.0045)	(0.0057)	(0.0072)	(0.0095)	(0.0140)
$\Delta_{\tau-1}$Emp	0.0685*	0.0719*	0.1149*	0.1182*	0.1333*	0.1596*	0.2130*	0.2440*	0.2549*	0.1939*

	***	***	***	***	***	***	***	***	***	**
	(0.0054)	(0.0079)	(0.0105)	(0.0132)	(0.0159)	(0.0204)	(0.0259)	(0.0323)	(0.0450)	(0.0703)
Age	-0.0320***	-0.0547***	-0.0629***	-0.0781***	-0.0850***	-0.0973***	-0.0940***	-0.1116***	-0.1126***	-0.1414***
	(0.0012)	(0.0017)	(0.0023)	(0.0029)	(0.0035)	(0.0044)	(0.0055)	(0.0070)	(0.0093)	(0.0137)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	72,882	62,910	51,660	41,568	32,572	24,496	17,822	12,430	7,698	3,656
Loans	36,441	31,455	25,830	20,784	16,286	12,248	8,911	6,215	3,849	1,828
R2	0.067	0.086	0.089	0.088	0.088	0.084	0.085	0.09	0.097	0.111

Panel C: Assets

	$\Delta_{\tau+1}$Assets	$\Delta_{\tau+2}$Assets	$\Delta_{\tau+3}$Assets	$\Delta_{\tau+4}$Assets	$\Delta_{\tau+5}$Assets	$\Delta_{\tau+6}$Assets	$\Delta_{\tau+7}$Assets	$\Delta_{\tau+8}$Assets	$\Delta_{\tau+9}$Assets	$\Delta_{\tau+10}$Assets
GLoan	0.0772***	0.0927***	0.0893***	0.0752***	0.0672***	0.0553***	0.0660***	0.0406***	0.0569***	0.0415*
	(0.0016)	(0.0024)	(0.0032)	(0.0040)	(0.0050)	(0.0062)	(0.0077)	(0.0099)	(0.0133)	(0.0201)
Assets$_{\tau-1}$	-0.0325***	-0.0411***	-0.0423***	-0.0439***	-0.0443***	-0.0403***	-0.0374***	-0.0314***	-0.0286**	-0.0273†
	(0.0011)	(0.0016)	(0.0022)	(0.0028)	(0.0034)	(0.0043)	(0.0054)	(0.0071)	(0.0095)	(0.0151)
$\Delta_{\tau-1}$Assets	-0.0342***	-0.0220**	0.0049	0.013	0.0189	0.0355†	0.0456†	0.0587†	0.1014*	0.0558
	(0.0048)	(0.0072)	(0.0096)	(0.0120)	(0.0152)	(0.0189)	(0.0238)	(0.0309)	(0.0418)	(0.0673)
Age	-0.0246***	-0.0385***	-0.0509***	-0.0647***	-0.0834***	-0.0968***	-0.1038***	-0.1228***	-0.1262***	-0.1482***
	(0.0011)	(0.0017)	(0.0022)	(0.0028)	(0.0035)	(0.0044)	(0.0055)	(0.0072)	(0.0096)	(0.0152)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

FE										
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	74,976	64,400	52,728	42,534	33,138	25,134	18,154	12,514	7,686	3,576
Loans	37,488	32,200	26,364	21,267	16,569	12,567	9,077	62,57	3,843	1,788
R2	0.073	0.068	0.06	0.054	0.056	0.057	0.053	0.053	0.055	0.067

The table reports an OLS regression on 1 to 10 years' growth in sales (Panel A), employment cost (Panel B) and total assets (Panel C) for guaranteed-loan beneficiaries and a matched sample of non-beneficiaries since the year of the matching. Matching is performed using coarsened-exact matching followed by propensity-score matching using all available control variables. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. $Sales_{t-1}$, Emp_{t-1}, $Assets_{t-1}$ are the logarithms of firm sales, employment cost, and total assets at time *t-1*. $\Delta_{\tau-1}Sales$, $\Delta_{\tau-1}Emp$, and $\Delta_{\tau-1}Assets$ are logarithmic growth in the relevant variables between time *t-2* and *t-1*. Age is the logarithm of firm age at time *t-1*. Robust standard errors are reported in round brackets. ***: p-value<0.1%, **: p-value<1%%, *: p-value<5%; †: p-value<10%.

Table 4: Instrumental-variable panel regression

	$\Delta_{\tau+1}$Sales		$\Delta_{\tau+1}$Emp		$\Delta_{\tau+1}$Assets	
	First stage	IV (2SLS)	First stage	IV (2SLS)	First stage	IV (2SLS)
# GLoans	2.2508***		2.2686***		2.2290***	
	(0.0915)		(0.0940)		(0.0900)	
GLoans amount	5.6691***		5.3580***		5.6026***	
	(0.9992)		(1.0599)		(0.9812)	
Age	0.00210***	-0.0702***	0.00204***	-0.0906***	0.00197***	-0.0477***
	(0.0002)	(0.0005)	(0.0002)	(0.0005)	(0.0002)	(0.0004)
GLoan		0.2859***		0.2582***		0.1549*
		(0.0719)		(0.0766)		(0.0726)
Year FE	Yes		Yes		Yes	
Firm FE	Yes		Yes		Yes	
Obs.	3,6[illegible]4,756		3,559,407		3,743,850	
Loans	32,871		32,332		33,019	
R2	0.024		0.028		0.015	
Underid. Test	736.019		709.881		744.518	
Weak id. Test	367.099		397.788		416.252	
Overid. Test	1.116		0.268		5.196	

The table reports an instrumental-variable two-way fixed-effect panel regression on the growth of sales, employment, and total assets. *Age* is the logarithm of firm age at time t-1. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. The variable is instrumented using two instruments defined at the region-year level: *#GLoans*, which is the number of guaranteed loans (source: EIF) divided by the number of existing companies (source: Eurostat); and *GLoans amount*, which is the amount of guaranteed loans (source: EIF) divided by the amount of all loans (source: Eurostat). Robust standard errors (clustered by firm) are reported in round brackets. The underidentification test is the Kleibergen-Paap rk LM statistic. The weak identification test is the Cragg-Donald Wald F statistic. The overidentification test is the Hansen J-statistic. ***: p-value<0.1%, *: p-value<5%.

Table 5: Credit-event analysis

Panel A: OLS regressions

	$\Delta_{\tau+3}$Sales	$\Delta_{\tau+3}$Emp	$\Delta_{\tau+3}$Assets
GLoan	0.0191***	0.0243***	-0.0250***
	(0.0038)	(0.0043)	(0.0037)
$\Delta_{\tau-1}$Y	-0.0556***	-0.0383***	0.0033
	(0.0040)	(0.0032)	(0.0022)
Age	-0.1099***	-0.1159***	-0.0914***
	(0.0010)	(0.0010)	(0.0008)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Obs.	852,616	807,566	873,474
Loans	12,749	12,417	12,859
R2	0.036	0.038	0.039

Panel B: 2SLS regression

	$\Delta_{\tau+3}$Sales	$\Delta_{\tau+3}$Emp	$\Delta_{\tau+3}$Assets
GLoan	0.8608*	0.5187*	0.5701
	(0.4217)	(0.2357)	(0.4966)
$\Delta_{\tau-1}$Y	-0.0547***	-0.0391***	0.0019
	(0.0041)	(0.0066)	(0.0024)
Age	-0.1109***	-0.1169***	-0.0921***
	(0.0021)	(0.0029)	(0.0022)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Obs.	842,781	798,482	863,334
Loans	12,687	12,360	12,795
F	1424.649	889.022	654.983
Underid. test	7.103	7.100	7.137
Weak id. test	123.79	119.601	123.731
Overid. test	0.101	2.778	1.248

The table reports OLS regressions (Panel A) and instrumental-variable 2SLS regression on 3-year growth in sales, employment, and total assets for a sample of companies experiencing a credit event (annual increase in total liabilities/average assets>5%). *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. $\Delta_{\tau-1}Y$ is the growth of the dependent variable in the pre-event year. Age is the logarithm of firm age at time *t-1*. Robust standard errors are reported in round brackets. In Panel B, *GLoan* is instrumented using: *# GLoans*, which is the number of guaranteed loans (source: EIF) divided by the number of existing companies (source: Eurostat); and

GLoans amount, which is the amount of guaranteed loans (source: EIF) divided by the amount of all loans (source: Eurostat). The underidentification test is the Kleibergen-Paap rk LM statistic. The weak identification test is the Cragg-Donald Wald F statistic. The overidentification test is the Hansen J-statistic. ***: p-value<0.1%, *: p-value<5%.

Table 6: Productivity analysis

	(1) CEM/PSM Matching	(2) Credit event OLS	(3) Credit event 2SLS IV	(4) Panel 2SLS IV
GLoan	0.0116***	0.0135***	0.2860	-0.0308
	(0.0017)	(0.0023)	(0.2210)	(0.0694)
$\Delta_{\tau-1}$TFP	-0.2665***	-0.3532***	-0.3519***	
	(0.0049)	(0.0023)	(0.0043)	
Age	0.0004	0.0043***	0.0038***	-0.0092***
	(0.0072)	(0.0004)	(0.0009)	(0.0004)
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No
Sector FE	Yes	Yes	Yes	No
Firm FE	No	No	No	Yes
Obs.	54,398	774,424	765,812	3,429,027
Loans	27,199	12,219	12,162	31,903
R2	0.148	0.110	0.095	0.002
Underid. Test			7.047	696.149
Weak id. test			118.909	386.869
Overid. Test			8.196	0.241

The tables report cross-sectional (Columns 1-3) and panel (Column 4) regressions on TFP growth. TFP is calculated using the Levinsohn and Petrin (2003) procedure by NUTS2 2-digit sector. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. $\Delta_{\tau-1}$*TFP* is the growth of TFP in the pre-event year. *Age* is the logarithm of firm age at time t-1. The dependent variable is the 3-year TFP growth in the cross-sectional regressions and annual TFP growth in the panel regressions. Column 1 includes beneficiaries and non-beneficiaries identified using coarsened-exact matching followed by propensity-score matching using all available control variables. Columns 2-3 include only companies experiencing a credit event (annual increase in total liabilities/average assets>5%). Columns 1-2 are OLS regressions, and Column 3 and Column 4 are IV regression in which *GLoan* is instrumented using: *#GLoans*, which is the number of guaranteed loans (source: EIF) divided by the number of existing companies (source: Eurostat); and *GLoans amount*, which is the amount of guaranteed loans (source: EIF) divided by the amount of all loans (source: Eurostat). Robust standard errors are reported in round brackets. The underidentification test is the Kleibergen-Paap rk LM statistic. The weak identification test is the Cragg-Donald Wald F statistic. The overidentification test is the Hansen J-statistic. ***: p-value<0.1%.

Table 7: Organic vs. external growth

	$\Delta_{\tau+3}$Sales	$\Delta_{\tau+3}$Emp	$\Delta_{\tau+3}$Assets
GLoan	0.0670***	0.0688***	0.0892***
	(0.0028)	(0.0031)	(0.0032)
$Y_{\tau-1}$	-0.0220***	-0.0592***	-0.0425***
	(0.0020)	(0.0024)	(0.0022)
$\Delta_{\tau-1}Y$	0.0499***	0.1149***	0.005
	(0.0101)	(0.0105)	(0.0096)
Age	-0.0714***	-0.0629***	-0.0508***
	(0.0020)	(0.0023)	(0.0022)
Acquisitions	0.075	0.1527**	0.2153*
	(0.0546)	(0.0467)	(0.0881)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Obs.	53,682	51,660	52,728
Loans	26,841	25,830	26,364
R2	0.081	0.089	0.06

The table reports OLS regressions on 3-year growth in sales, employment, and total assets for guaranteed-loan beneficiaries and a sample of non-beneficiaries matched using CEM followed by PSM. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. $Y_{\tau-1}$ is the level of the dependent variable in the pre-treatment period. $\Delta_{\tau-1}Y$ is the growth of the dependent variable in the pre-treatment year. *Age* is the logarithm of firm age at time *t-1*. Acquisition is the number of acquisitions made in the three years following the signature year. Robust standard errors are reported in round brackets. ***: p-value<0.1%, **: p-value<1%, *: p-value<5%.

Table 8: Moderating effects of age and size on growth in the three years following the guaranteed loan

	(1) $\Delta_{\tau+3}$Sales	(2) $\Delta_{\tau+3}$Emp	(3) $\Delta_{\tau+3}$Assets	(4) $\Delta_{\tau+3}$Sales	(5) $\Delta_{\tau+3}$Emp	(6) $\Delta_{\tau+3}$Assets
GLoan	0.0634***	0.0613***	0.0820***	0.0531***	0.0488***	0.0587***
	(0.0032)	(0.0034)	(0.0037)	(0.0034)	(0.0036)	(0.0040)
Young	0.0046	0.0038	0.0140*			
	(0.0059)	(0.0066)	(0.0069)			
GLoan x Young	0.009	0.0193**	0.0176*			
	(0.0061)	(0.0069)	(0.0069)			
Small				-0.0149**	-0.1192***	-0.1018***
				(0.0055)	(0.0056)	(0.0054)
GLoan x Small				0.0318***	0.0435***	0.0588***
				(0.0058)	(0.0065)	(0.0065)
$Y_{\tau-1}$	-0.0219***	-0.0591***	-0.0423***	-0.0212***	-0.0949***	-0.0671***

	(0.0020)	(0.0024)	(0.0022)	(0.0030)	(0.0031)	(0.0027)
$\Delta_{\tau-1}Y$	0.0513***	0.1171***	0.0066	0.0513***	0.1194***	0.0124
	(0.0101)	(0.0105)	(0.0096)	(0.0101)	(0.0104)	(0.0096)
Age	-0.0669***	-0.0561***	-0.0396***	-0.0712***	-0.0649***	-0.0524***
	(0.0033)	(0.0036)	(0.0037)	(0.0020)	(0.0023)	(0.0022)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	53,682	51,660	52,728	53,682	51,616	52,554
Loans	26,841	25,830	26,364	26,841	25,811	26,303
R2	0.081	0.089	0.06	0.081	0.098	0.066

The table reports OLS regressions on 3-year growth in sales, employment, and total assets for guaranteed-loan beneficiaries and a sample of non-beneficiaries matched using CEM followed by PSM. *GLoan* is an indicator variable equal to 1 when beneficiaries obtain a guaranteed loan. $Y_{\tau-1}$ is the level of the dependent variable in the pre-treatment period. $\Delta_{\tau-1}Y$ is the growth of the dependent variable in the pre-treatment year. *Age* is the logarithm of firm age at time t-1. *Young* is a dummy variable equal to 1 for companies with below-median age. *Small* is a dummy variable equal to 1 for companies with below-median total assets. Robust standard errors are reported in round brackets. ***: p-value<0.1%, **: p-value<1%, *: p-value<5%.