

Have Covid-19 state-guaranteed loans fulfilled their purpose?

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Abstract

This paper analyses the mid-term effects of French state-guaranteed loans on financial statements and corporate default risk using a triple difference-in-differences method. The COVID-19 pandemic disrupted the economy. As a result, most governments launched a wide range of support for vulnerable individuals and firms. The French program studied enabled companies to benefit from loans with the primary objective of preventing the bankruptcy of companies that had previously been solvent. Using a unique dataset, we show that companies participating in the program were more liquid in the short term but not until state-guaranteed loans (SGL) full reimbursement compared to non-participants. We observe that, despite the reduction in the number of bankruptcies during the COVID-19 crisis, the default risk increased during the crisis and that companies participating in the program bankrupt more often after the COVID-19 crisis than non-participating companies. Based on Altman Z'-score ratios, we propose an updated default score to consider the higher risk related to SGL.

JEL Classification: G01, G18, G32, G33, G38, H12, H81.

Keywords: Corporate bankruptcy, COVID-19, Triple difference-in-differences, Government policy, Liquidity management, Financial statements, State-Guaranteed Loans.

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1.Introduction

A high corporate distress regime is mostly unpredictable, yet not uncommon, both globally and over time. It can occur for various reasons during or following crises such as the 1995 Mexican crisis, the 1997 Asian crisis, the dot-com bubble/burst of 2000–01, the global financial crisis of 2007–08 and the European debt crisis of 2012 (Hacidebel & Qu, 2022). A high corporate distress regime can lead to numerous firm bankruptcies and have multiple consequences for governments and individuals. The most recent global period of high corporate distress began in 2020 with the onset of the Covid-19 pandemic and is still evident in some countries as of 2025. During a crisis, firms try to continue operating without going bankrupt. However, if the crisis is severe, they may not be able to succeed without government intervention. This is what happened to avert looming catastrophes during the pandemic. The government implemented support measures to provide liquidity and stabilize intermediation, to avoid corporate bankruptcy and the subsequent impact on national economies and global growth prospects (OECD, 2021).

During the crisis (2020-2021), we observe an abnormally low number of bankruptcies. This is explained by the substantial government support measures implemented in response to the Covid-19 crisis (WTO, 2024). Amongst the most effective program features, debt guarantees improved market confidence, allowing for stronger recovery and lower cash outflows by easing firms' access to credit. The characteristics of state-guaranteed loan (SGL) programs vary by country (Cao et al., 2024).

In response to the economic shock caused by the Covid-19 pandemic, the French government introduced the SGL scheme to support struggling firms by providing access to liquidity and reducing the risk of bankruptcy during and after the crisis (*Cour des Comptes*, 2023). Between 2020 and 2022, France granted €144 billion in SGL, with more than 90% of this amount granted in 2020 alone. This measure was the most significant business support initiative during the pandemic, surpassing solidarity funds (€41 billion), deferral of social security contributions (€26 billion), furlough schemes (€22 billion), and exemptions from social security contributions (€8.5 billion). The total

amount of support provided was 249.7 billion euros, equivalent to 10.9% of France's 2020 gross domestic product (*Cour des Comptes*, 2023; *France Stratégie*, 2021).

The French SGL program offered favorable terms with flexible repayment options (Lé et al., 2024). The loan included a 12-month deferral for repayment with an option for early repayment. The company had to repay its state-guaranteed loan within a maximum of six years from the date it was granted. Depending on loan duration, interest rates ranged from 0.25% in the first year to a maximum of 2.5%. The state guaranteed between 70% and 90% of each loan, aligning the interests of banks, firms, and the government while reducing moral hazard. The rejection rate for SGL applications remained low at around 2.9%, which was below the typical rate for cash loans. For many firms, SGL offset the decline in gross operating surplus, temporarily replacing other bank loans, particularly in Q2 2020 (*Cour des Comptes*, 2023).

One-third of the SGL had been repaid by the end of 2022. This figure rose to 62% by June 2024 and to 86% by September 2025. From 2022 until 2026, firms facing financial difficulties had been allowed to restructure their SGL for an additional two to four years, extending the repayment period to 2030. This extension was subject to approval by banks and the national credit mediator¹. In this case, the service helped facilitate debt restructuring, including SGL. As of June 2025, 56% of mediation requests had been accepted (*Assemblée Nationale*, 2025). However, restructured SGL loans from firms might be reclassified as non-performing in bank accounts. This could result in a downgrade of the firm's default risk grade by the *Banque de France* and limit its access to future financing.

Despite these government support measures; there has been a surge in business bankruptcies following the crisis. According to Eurostat (2025), bankruptcy levels in European countries have exceeded pre-pandemic figures, with France, Belgium, Germany, Spain, the Netherlands, and Austria experiencing a record number of

¹ The *Banque de France* provides credit mediation services to assist companies experiencing difficulties with their financial partners, including banks, credit insurers, factors, and credit providers.

bankruptcies in 2024. The *Banque de France* (2025) indicates a further deterioration in France in 2025. This unexpected and severe trend raises concerns about the medium-term impact of SGL on firm viability.

Therefore, understanding the repayment capacity of firms that benefit from SGL is critical for policymakers and financial institutions (Blanc et al., 2024). The increase in corporate debt introduces uncertainty regarding firms' ability to meet their obligations without compromising business sustainability or market stability. The French government estimates that net losses to public finances related to state guarantees will amount to 3.6 billion euros by 2030. (*Cour des Comptes*, 2023).

The SGL program was designed to ensure balanced risk and cost allocation amongst firms, banks, and the state. For firms, its key objectives were to address immediate liquidity needs and support medium to long-term survival. This paper examines whether these objectives were met and explores the broader implications of the SGL program on corporate financial health in the post-pandemic period.

This article aims to help policymakers, financial institutions, companies, and other stakeholders gain a deeper understanding of the implications of government support for firms after a crisis. Specifically, the article addresses key questions about the impact of SGL in the context of the French government's response to the pandemic.

- Do SGL beneficiaries have the same level of liquidity after the crisis as before? How do SGL beneficiaries' liquidity levels compare to non-SGL beneficiaries?
- Do SGL beneficiaries have a greater risk of default than non-beneficiaries after the crisis? Do SGL beneficiaries have a greater bankruptcy rate than non-beneficiaries after the crisis?
- Do discriminant score models demonstrate improved default risk prediction performance when SGL status is included?

This study uses a triple difference-in-differences (TDD) approach, which is a methodology used to evaluate policy effectiveness. Unlike the traditional double difference-in-differences (DiD) framework, which accounts for two time periods, the

triple DiD design incorporates an additional pre-period of comparison. This additional period strengthens causal inference by controlling for pre-intervention heterogeneity that could bias estimates in a standard DiD framework.

Leveraging this richer structure enables our analysis to robustly identify the impact of SGL measures on firms' liquidity and bankruptcy risk. This advancement is particularly relevant in contexts where effects may vary across multiple dimensions, such as time. The triple difference-in-differences model is a valuable tool in these contexts because it does not require parallel trends assumption to be valid.

To further strengthen the analysis, we complement the TDD estimation with a logistic regression that integrates the SGL dummy variable in Altman Z' score to predict bankruptcy outcomes. This combined approach improves the performance of our findings and offers a new perspective on the effectiveness of SGL policies. Our empirical application utilizes a unique dataset from COFACE, a leading trade credit insurer, which provides detailed information on the credit and bankruptcy of individual firms. This rich data source allows us to rigorously test whether SGL fulfills its intended purpose of maintaining liquidity and mitigating bankruptcy.

This paper finds that state-guaranteed loans provided an initial liquidity buffer for beneficiary firms during the COVID-19 crisis, primarily by increasing their cash holdings. However, this advantage was not sustained over the medium term compared to non-beneficiaries. By 2023, SGL beneficiaries were no more liquid than non-beneficiaries. Regarding bankruptcies, France experienced a temporary decline in bankruptcy numbers during the early years of the crisis. However, a sharp catch-up effect occurred from 2022 onward. SGL firms' default risk increased slightly during the crisis due to increased debt. SGL firms exhibited higher bankruptcy rates after the crisis, suggesting that SGL delayed but did not prevent bankruptcy for vulnerable firms. To better capture these dynamics, we updated the Altman Z'-score to include an SGL treatment dummy, thereby enhancing its predictive power in crisis contexts.

The rest of the paper is organized as follows. Section 2 provides background on the SGL knowledge and hypotheses. Section 3 presents the empirical setting, including the data. Section 4 describes our results. We conclude the paper in Section 5.

2.Literature Review and Hypotheses

The literature on state-guaranteed loans is a growing field (Cao et al., 2024; Crawford et al., 2024; Santero-Sánchez et al., 2024; Thanasas et al., 2024). Studies on SGL have primarily focused on market failures due to information asymmetry, credit rationing, adverse selection, and moral hazard theories that explain empirical observations. Themes have diversified to include amongst others firm performance, risk management, cost of debt and credit allocation. SGL can be implemented during a crisis period or outside of it to enable firms to obtain credit or improve the terms and conditions under which they can borrow (Caselli et al., 2021). Few studies have been conducted before, during, and after the Covid-19 crisis in France (Barrot et al., 2024; Dautovic & Hsieh, 2025), other countries (Bajo et al., 2025), and comparatively (Massoc, 2021). The literature review attempts to answer the following question: How do SGL affect corporate liquidity, risk of default, and bankruptcy rate?

2.1.Credit access and firm liquidity

During the pandemic, firms' access to financing tightened, leading them to adapt their strategies. Gull et al. (2023) find that SMEs that adopted better strategies during the credit crunch were more likely to receive new credit from the government and commercial banks. In the US, Bachas et al. (2020) confirm that the efficiency of lending guarantees depends on whether the guarantees increase the supply of lending or simply act as a subsidy for lenders. This is measured by the elasticity of credit provision to the loan guarantee. Additionally, Beyhaghi (2022) shows that government-guaranteed loans have the greatest impact on interest rates in the US. This is compared to other third-party credit guarantees, such as corporate and personal agencies. Banks are willing to provide a discount on guaranteed loans because credit guarantees mitigate risk. On average, guaranteed loans have a lower bank-estimated loss given default ratio

and are less likely to become non-performing than similar non-guaranteed loans. The loan guarantee program reduces the cost of debt and increases the supply of loans. However, the proportional effects of one unit of collateral guarantee are not uniform across all firms (Cowling et al., 2018; Ughetto et al., 2017).

The goal of the state-guaranteed loan program in France was to support distressed firms during the Covid-19 crisis by providing access to liquidity through guarantees to mitigate the risk of bankruptcy during and after the crisis (*Cour des Comptes*, 2023). However, the response to companies' liquidity needs has often exceeded what was necessary. In some cases, state-guaranteed loans offset the fall in gross operating surplus more than necessary for the companies that received them. Foreau et al. (2024) demonstrate that companies participating in the SGL program increased their debt and cash holdings more than others during the COVID-19 crisis, due to precautionary borrowing and cash buffering. Guillou et al. estimate that around 24.5% of companies overcompensated for their loss of liquidity with subsidies. Taking the SGL into account increases the total number of companies that overcompensated for loss of liquidity to 39%, with nearly €73.4 billion in guaranteed loans allocated in excess of liquidity needs. These companies are mainly located in the wholesale and retail trade, manufacturing, and culture and leisure sectors. Bach et al. (2021) and Epaulard et al. (2021) confirm that SGL use eliminated the risk of short-term illiquidity for French companies during the crisis.

In their study, Bach et al. (2021) measure liquidity as the sum of cash and marketable securities relative to total assets. Epaulard et al. (2021) define liquidity as the change in checking account balances. The liquidity of non-SGL beneficiaries also increases, but by a smaller amount. Studies on SGL liquidity mainly focus on cash, omitting other components of current assets, such as receivables and inventory. Furthermore, although research on the consequences of SGL in France during the 2020–2021 COVID-19 pandemic is available, studies on the period that followed are scarce. Using multiple liquidity measures, we examine how SGL achieved its objective of providing participating firms with access to liquidity. First, we compare the liquidity of

participants with that of non-participants. Then, we observe changes in the liquidity of participating firms over time to see if their liquidity was affected by the crisis. We verify whether SGL enabled beneficiary companies to maintain their pre-crisis liquidity levels during and after the crisis. Given SGL's objective to ensure corporate liquidity, we estimate that businesses that subscribed to SGL maintained their liquidity during and after the crisis compared to before. Due to the uncertainties and tightening credit conditions during the pandemic, we anticipate that companies that did not benefit from state-guaranteed loans were unable to maintain liquidity.

2.2.Bankruptcy paths and SGL credit allocation

The path of corporate insolvency is specific to the type of insolvency and the country in which the company operates. Stef and Bissieux (2022) study the resolution of corporate insolvency in France during the Covid-19 pandemic. In France, corporate insolvency can be resolved through four legal procedures: amicable liquidation, judicial liquidation, and two types of restructuring procedures, one for non-bankrupted firms and one for bankrupted firms. The study emphasizes the importance of encouraging amicable liquidation during and after the pandemic because it accelerates the allocation of assets to more successful firms. However, judicial liquidation can be a solution for firms severely affected by the crisis, preventing them from becoming "zombie" companies. Without resolution of corporate insolvency, this can lead to the perpetuation of zombification. Zombie firms are defined as mature, consistently underperforming firms that are unable to repay their debt but survive due to subsidized bank credit. Veganzones and Severin (2025) demonstrate that a state guaranteed loan can contribute to persistent zombification when banks misallocate credit to firms that are not expected to recover. Once SGL are no longer available, companies then go bankrupt. These findings demonstrate that bankruptcy is a complex phenomenon and that the allocation of SGL can have negative impacts on companies and the economy.

Several factors may explain the misallocation of SGL loans. Martin et al. (2025) demonstrate through a Spanish case study that banks faced distorted incentives, leading to suboptimal guarantee allocation. The measure was intended to maximize debt-

related profits and control over existing customers. Riskier and captive companies received a larger share of guaranteed credit. For those already customers of the bank, SGL resulted in increased indebtedness and higher levels of non-performing loans. Altavilla et al. (2025) show that, in four European countries (including France), the SGL supported bank lending by transferring default risk to governments. The substitution was most significant amongst riskier and smaller firms in the most affected sectors, as well as amongst the strongest banks. Cowan et al. (2015) find that the higher bankruptcy rates observed amongst firms selected for these programs in Chile must be the result of adverse selection. Lagazio et al. (2021) study the impact of expanding SGL criteria and find that relaxing access conditions negatively affected admitted firms. These effects included a rise in debt payback periods, a worsening balance between current assets and current liabilities, an increase in borrowing costs, and a greater weight of interest expenses on sales. In Italy, de Blasio et al. (2018) find that the program increased the likelihood that a firm would be unable to repay its loans. Foreau et al. (2024) demonstrate through a French study that despite the reduction in bankruptcy during the crisis, companies participating in the program had a higher default risk after the COVID-19 crisis than before and compared to non-participants. Guillou et al. (2023) demonstrate that less productive firms benefited the most from SGL in France during the Covid-19 crisis. However, the results of Nicolas et al. (2023) in France suggest that the partial public guarantee encouraged banks to lend according to their usual risk criteria, maintaining their standards for screening new loans, and did not prompt banks to increase their risk-taking. These findings show that the literature on banks' loan allocation choices yields mixed results regarding misallocation versus normal allocation. This highlights the risks associated with SGL.

2.3.Risk of default, prediction and bankruptcy rate

Blanc et al. (2024) demonstrate that corporate bankruptcy has increased in France since 2023 due to slowing growth, rising production costs, and tighter financing conditions. They also show that, as of 2024, repayment dynamics are highly heterogeneous. Companies' repayment capacities are measured by cash levels and cash

flow. Overall, 7.5% of companies that have taken out a state-guaranteed loan would have difficulty repaying it, representing a default risk of around 4% on the total amount of state-guaranteed loans. The study suggests that the expected non-repayment rate could be much higher if the companies' self-financing capacity is insufficient. The study also suggests that the expected non-repayment rate could be more than double the rate estimated by the *Banque de France*, due to the companies' lower self-financing capacity than that simulated. The deadline for full repayment of the SGL is 2026 for most companies, raising questions about the ongoing consequences for the economy, businesses, and society in the event of high bankruptcy rates.

To better predict corporate default risks, it is essential to determine which variables to include in the models (Du Jardin, 2009). Séverin and Veganzones (2023) analyze the determinants and trajectories of bankruptcy, as well as current issues associated with forecasting models. They conclude that financial ratios are essential to bankruptcy prediction studies. In many cases, including non-financial variables in bankruptcy score prediction improves model performance. Over the last sixty years, predicting business failure has become a major research domain within corporate finance (Veganzones & Severin, 2021). The most popular methods are cross-sectional, capturing different predictive elements in one value. Over time, we have seen the emergence of various explainable models, such as the univariate discriminant analysis model, the multiple discriminant analysis, the logit analysis, and the probit analysis. Z-score models offer simplicity, interpretability, and low cost, which facilitates their adoption (Braunsberger & Aschauer, 2025; Dasilas & Rigani, 2024). Including non-financial variables in models also enables a more comprehensive evaluation of a firm's financial health and improves model performance. However, we did not identify any model that considered the benefits of state-guaranteed loans variable when predicting firm defaults risks.

2.4.Synthesis

According to the literature, state-guaranteed loans affect liquidity and bankruptcy rates. SGL participants often increase liquidity and overcompensate for the loss of liquidity due to the crisis. The impact of guaranteed loans on balance sheet structure

varies depending on economic conditions and firm characteristics. Default risk increases for SGL beneficiaries for several reasons, including easy access conditions, the participation of less productive firms. This study attempts to address an existing gap in the literature by analyzing a set of French companies and providing evidence of the medium-term impact of SGL on financial statements. The study also analyzes subsequent bankruptcy following the Covid-19 crisis. The study demonstrates that SGL impacts liquidity during a crisis and affects the bankruptcy rate. It proposes new firm default risk prediction models that integrates the SGL variable. After reviewing the literature and previous arguments, we formulate eleven hypotheses.

Hypothesis 1: SGL participants are less liquid than SGL non-participants before the crisis.

Hypothesis 2: SGL has a positive effect on the liquidity of participants during the crisis.

Hypothesis 3: SGL participants are more liquid during the crisis than SGL non-participants.

Hypothesis 4: SGL has a positive effect on the liquidity of participants after the crisis.

Hypothesis 5: SGL participants are more liquid after the crisis than SGL non-participants.

Hypothesis 6: SGL participants are more at risk of default than SGL non-participants before the crisis.

Hypothesis 7: SGL increases the risk of default of participants during the crisis.

Hypothesis 8: SGL participants are more at risk of default during the crisis than SGL non-participants.

Hypothesis 9: SGL increases the risk of default of participants after the crisis.

Hypothesis 10: SGL participants are more at risk of default after the crisis than SGL non-participants.

Hypothesis 11: SGL dummy negatively impacts the score of firms in the default score prediction model.

3.Data and Methodology

3.1.Data

We use three databases provided by COFACE, one of the world’s top three trade credit insurers. The first includes financial statements of French companies from 2015 to 2023, including confidential accounts. The second includes corporate legal bankruptcies in France from 2020 to 2025. The third database, collected from COFACE’s Enhanced Information Centers, is a set of detailed financial analysts’ reports from 2020 to 2025. They are elaborated by COFACE’s credit analysts through interviews, confidential and publicly available information. Some of these reports from 2020 to 2025 contain information enabling us to identify companies that have raised an SGL. Detailed SGL information is scarce, because it is only detained by the government and partially by banks. To identify SGL beneficiaries, we list different text patterns corresponding to SGL subscription usual terminologies (e.g.: PGE, state-guaranteed loan, government-backed loan, etc.) to create an automatic detection by regular expression.

Then, we manually check each of the positive results to recategorize false positives. As a result, 2039 companies have reports identifying the subscription of an SGL (“Yes” group); 431 companies have reports confirming the absence of SGL (“No” group) and there are 13284 companies for which reports do not confirm or deny the fact of having benefited from an SGL (“Unknown” group).

Public statistics inform us that 17% of companies have taken an SGL between 2020 and 2022. Internal Coface reports during this period focused significantly on SGL-related information. We therefore assume that the companies for which the report have no information about SGL are those that have not taken an SGL. In fact, the comments focus on the main new characteristics of companies since the last report.

In the analysis of the impact of SGL, the two groups "No" and "Unknown" will be grouped under the name “Non-participants (No/Unknown)”. This hypothesis is validated by the empirical study, the methodology of which is developed below, which shows that there is no statistically significant difference between “no” and “unknown”

companies in terms of changes in liquidity and default during the SGL allocation period (see Appendix 1).

By combining these three private databases, consisting of financial statements, corporate legal bankruptcy, and SGL identifiers, we are creating a new, unique database that allows us to assess the impact of SGL on companies. The final dataset comprises 3943 companies for which we have financial statements from 2015 to 2023 and one expert report. We aggregate results by activity sectors and sizes, to ensure confidentiality.

Table 1 shows the distribution of companies by sector, with 81% belonging to four sectors: construction (F), manufacturing (C), wholesale, retail trade and repair of motor vehicles and motorcycles (G), Professional, scientific and technical activities (M). Although the dataset includes many other sectors, only a few companies are represented in each. Small, medium and mid-cap companies represent 96% of the dataset, which is higher than the proportion of such companies in France. In 2019, before the crisis the distribution is comparable between businesses participating and not participating in the state-guaranteed loan scheme (Table 2). The majority of companies did not take on bank debt in 2019. Companies that participated in SGL during the crisis were slightly more indebted before the crisis than those that did not participate. The bank debt to be repaid is low for both groups. Liquidity ratios are similar, with slightly more liquidity for companies that subsequently participated in the SGL program. According to Altman's Z and Z' scores, the probability of default is higher for companies that choose to take out SGL than for those that do not.

INSERT TABLE 1

INSERT TABLE 2

3.2. Triple difference-in-differences method

Causal inference is a key challenge to evaluate public policy (Wing et al., 2018), when randomized controlled trials are infeasible. The difference-in-differences (DiD) design is a quasi-experimental alternative, trending in econometrics literature (Roth et al., 2023).

DiD is a statistical technique that estimates the causal effect of a treatment by comparing the changes in outcomes over time between a treated group and a control group. The fundamental idea behind DiD is to observe the difference in outcomes between two periods (before and after the treatment) between the two groups (treated and untreated).

Difference-in-differences regression is defined as follows:

$$Y_{\text{DiD}} = \beta_0 + \beta_G * [\text{Treated}] + \beta_T * [\text{Time}] + \beta_{GT} * [\text{Time Treated}] + \varepsilon$$

Y_{DiD} is the outcome. The treatment status is defined by $[\text{Treated}]$ dummy, the period status is defined by $[\text{Time}]$ dummy, and the treatment effect is isolated by $[\text{Time} * \text{Treated}]$ dummy. Each has a corresponding β representing the regression coefficient of each group effect.

The treatment effect estimate is:

$$\begin{aligned} \beta_{GT} = & (\text{treated group after treatment} - \text{treated group before treatment}) \\ & - (\text{untreated group after treatment} - \text{untreated group before treatment}). \end{aligned}$$

The two-group two-period DiD design is intuitive, but it does not accommodate the complexity encountered in all applications. Before applying DiD, key assumptions must be validated. In applied work, the most challenging task is evaluating the credibility of the parallel trend assumption because it cannot be statistically proven. It can only be observed through graphical evidence before and after treatment. Additionally, the post-treatment trend cannot be observed due to data unavailability after 2023.

The parallel trend restriction implies that before treatment, the outcome trends for each group should differ only by a constant amount and should follow the same pattern of period-specific changes. In other words, if you plot the time series for each group, the lines should be parallel for each period. Parallel lines do not have to be linear. Time-fixed effects allow for flexible trends that can shift up or down across periods. The model provides an unbiased estimate of the average treatment effect on the treated only if this assumption holds. If parallel trend assumption is violated, the estimated

treatment effect may reflect unobserved factors and confounding influences, making the result biased.

To face these major parallel trends assumption challenge, researchers can use alternative methods such as synthetic control groups or propensity score matching (PSM) in a first step and then estimate treatment effects using DiD method on the matched sample, augmented DiD regression (Hansen et al., 2017) or triple difference-in-differences (TDD). We chose the triple-difference (DDD) approach because it eliminates concerns about the parallel trend assumption, which no longer needs to be verified. Among the available alternatives, this method allows us to retain pre-program data, which we can leverage to reduce bias. Difference-in-difference-in-differences design is also called triple-difference or triple difference-in-differences (Baker et al., 2026; Chen et al., 2020; Gruber, 1994; Olden & Møen, 2022; Ortiz-Villavicencio and Sant’Anna, 2025; Strezhnev, 2024).

TDD uses an additional comparison group before treatment. The triple-difference estimator can be computed as the difference between two difference-in-differences estimators. By subtracting one DiD estimate from the other—forming a triple-difference—researchers can remove the bias from the confounder and isolate the treatment effect (Atanasov and Black, 2016). Even though the triple difference is the difference between two difference-in-differences, it does not need two parallel trend assumptions. The intuition is that the difference between two biased difference-in-differences estimators will be unbiased if the bias is the same in both estimators. It requires the relative outcome of groups in the first DiD state to trend in the same way as the relative outcome of groups in the second DiD, in the absence of treatment.

Difference-in-difference-in-differences regression is defined as follows:

$$Y_{TDD} = \beta_0 + \beta_1[SGL] + \beta_2[t_1 + 2t_2] + \beta_3[(t_1 + 2t_2)*SGL] + \beta_4[t_2] + \beta_5[t_2*SGL] + \epsilon$$

Y_{TDD} is the outcome. The treatment status is defined by $[SGL]$ dummy. The period status is defined by $[t_1]$ dummy for year just prior treatment and $[t_2]$ dummy year after

treatment. Each has a corresponding β representing the regression coefficient of each group effect. See Figure 1 for a visual representation.

INSERT Figure 1

β_0 : Average outcome level (Y) for the control group (non-SGL) before any intervention.

β_1 : Average difference between the control and treatment groups at T_0 (group effect).

β_2 : Average time effect on the control group at T_1 relative to the reference period at T_0 (time effect).

β_3 : Average additional effect for the treatment group at T_1 relative to the control group (group $\times$ time interaction). Absorbing the effect of parallel trend violation.

β_4 : Average additional effect on the control group at T_2 (post-intervention: T_2).

β_5 : Average additional effect for the treatment group at T_2 compared to the control group (triple interaction: group $\times$ t2). Corresponding to treatment effect.

We estimate that the effects observed in the first DiD analysis are twice as large in the second DiD because it is after two periods. We use an equal duration before and after the intervention (meaning $T_1 - T_0 = T_2 - T_1$). This structure ensures temporal balance in estimating treatment effects through bias estimates. In all regressions in our study, the year $T_1 = 2019$ is fixed, which represents the year immediately preceding the Covid-19 crisis. Pre-program corresponds to T_0 , before treatment to T_1 , and after treatment to T_2 . The years used in our TDD vary across regressions and are paired as follows:

INSERT TABLE 3

The treatment effect estimate is:

$$\begin{aligned} \beta_5 = & ((\text{treated group after treatment} - \text{treated group before treatment}) \\ & - (\text{untreated group after treatment} - \text{untreated group before treatment})) \\ & - ((\text{treated group before treatment} - \text{treated group pre-program}) \\ & - (\text{untreated group before treatment} - \text{untreated group pre-program})). \end{aligned}$$

3.3.Default prediction model

We will use the default metrics of Altman (1968, 1993) models considering data available and complementary advantages and drawbacks of each method (Foreau et al., 2024). Although the data used for these tests is over 60 years old, the Altman Z-score model is still in use. The model correctly classified a high proportion of cases, with low Type I and Type II errors (Altman, 2013). We use Altman Z and Z'-score for TDD.

We also update the score with a new, recent French database. There are several reasons why a revised Z'-score classification model could improve upon and build on the statistical models published in the previous decade. The revised model should be as relevant as possible to the population to which it will eventually be applied (size, sector, country, financial profile, period, business failure type and annual reporting standard). Updating the default score can also make it possible to incorporate new statistical methodologies, increase the sample size used to create the model, create more general models (so that there are no longer several models depending on the type of business), and keep up to date with the temporal nature of the data to make the model relevant to past bankruptcies, but also for data that will appear in the future.

To assess the impact of SGL on the probability of default over a one year horizon, we will perform a logistic regression (LR). This will follow Altman's (2013) methodology to revisit the score, using the Altman Z' score variables and including the SGL dummy variable. We do not adjust the threshold score with a zone of ignorance. While the evaluation of the reference sample is consistent for explanatory purposes, as Altman suggests, it produces optimistic metrics due to the lack of out-of-sample validation.

We did not re-estimate the models using multivariate discriminant analysis, as originally employed by Altman. This method is generally considered to be less reliable than logit regression (Press & Wilson, 1978) because it makes two restrictive assumptions: that the explanatory variables follow a multivariate normal distribution and that the covariance matrices of bankrupt and non-bankrupt firms are equal. In contrast, logit regression is more robust, as it does not require normality assumptions (Cunha et al., 2025). Nevertheless, it is established that logistic regression exhibits poor performance when applied to highly imbalanced datasets, particularly when the

minority class is the focal point of analysis. This issue is salient in our study and could result in an underestimation of the conditional probability of belonging to the minority class, resulting in elevated Type I error rates—failing to identify firms that will default.

The linear regression function transforms the values of the individual variables into a single z-score. It is primarily used to classify and make predictions in cases where the dependent variable is qualitative (in our study: bankrupt or non-bankrupt). We force the proportion of state-guaranteed loans in the group of non-bankrupt companies to be proportional to our sample and the intercept to zero. The logistic regression estimates coefficients by maximizing likelihood, without assuming any distribution of the predictors.

In our case, the ratios are chosen following the Altman Z'-score, which is used as a baseline for comparison. The Altman study selected five variables from the original list of twenty-two that performed the best overall in predicting corporate bankruptcy. The greater a firm's distress potential, the lower its discriminant score.

Altman Z'-score use the following ratios:

X1 = working capital/total assets,

X2 = retained earnings/total assets,

X3 = earnings before interest and taxes/total assets,

X4 = book value of equity/total liabilities,

X5 = sales/total assets

the model does not contain a constant (Y-intercept) term.

In our study, we include X6 = SGL dummy.

After estimating the values of the discriminant coefficients, we can calculate discriminant scores for each observation in the sample or for any firm. Then, we can assign observations to one of the groups based on this score. The procedure essentially involves comparing the profile of an individual firm with those of the alternative groupings.

Recognizing that the sample is not homogeneous, we carefully selected firms. We eliminate micro-enterprises and large enterprises to limit the effects of size on data distribution. To eliminate outliers, we exclude companies for which at least one of the five ratios is less than 5% or greater than 95% of the sample. Group 1 consists of bankrupt firms with financial statements from one year prior to bankruptcy. We examined the sample of firms in each group using data from one financial statement prior to distress. Group 2 consists of a paired sample of nonbankrupt firms chosen via stratified random sampling by financial statement year, sector and size.

4. Results

In the following sections devoted to the results, we first present the main tests of the hypotheses before concluding with a discussion on robustness to answer our main question: « Have SGL enabled companies to maintain their liquidity and avoid bankruptcy in the medium to long term? ». Next, we present statistics on corporate bankruptcies between 2020 and 2025, which allow us to update Altman's Z'-score in our case study. Figure 2 represents the evolution of the variables studied for firms participating in SGL versus firms not participating in SGL between 2015 and 2023.

INSERT FIGURE 2

4.1. Main results

4.1.1. Indebtedness

The triple difference-in-differences results between participating and non-participating enterprises are summarized in tables 4, 5 and 6. To simplify the presentation of results, we designate the regressions for the different sub-periods by the year following treatment (T_2), i.e. 2020 to 2023.

In 2020, companies that benefited from state-guaranteed loans signed up for more debt than those not benefiting from them (β_5). This result confirms the relevance of the firm groupings performed. After 2020, the coefficients are negative, and no significant differences between participating and non-participating enterprises can be observed.

This shows that the increased demand occurred over a short period of time. The loan made it possible to avoid restricting access to credit when needed.

As a result, companies benefiting from state-guaranteed loans show much higher levels of bank debt relative to their total assets than non-beneficiaries from 2020 onwards (β_5). We can see that the difference in debt ratios is narrowing over time, indicating that the debt taken on is gradually being repaid. The fall in bank debt is greater between 2020 and 2021 than in subsequent years. This is because the loan can be partly repaid early after one year or two, and repayment is then linear. This is confirmed when we look at debt due within less than one year in 2020 compared to subsequent years.

INSERT TABLE 4

4.1.2. Liquidity

State-guaranteed loans were introduced as an emergency policy tool to safeguard corporate liquidity during the COVID-19 crisis. This enabled firms to cover usual expenses and absorb unexpected shocks without defaulting. We examine whether SGL effectively enhanced liquidity during and after the pandemic by comparing beneficiary and non-beneficiary firms from 2020 to 2023. Table 5 summarizes the triple-difference estimates of the cash, quick, and current ratios.

Before 2020, SGL participants showed lower cash ratio (β_1 and β_3), compared to non-participants. In 2020, all three liquidity ratios indicated that non-SGL and SGL firms had significantly strengthened their liquidity positions (β_4), which was consistent with the adoption of precautionary cash management strategies and reduction of short-term liabilities. Firms that benefited from state-guaranteed loans recorded a larger increase (β_5), reflecting direct cash inflows and cash buffering. These patterns confirm that SGL funds were effectively deployed to achieve the program’s primary short-term objective: securing liquidity and mitigating immediate default risk.

In the years following the COVID-19 crisis (2021 onward), firms maintained liquidity levels significantly above pre-crisis benchmarks across all three ratios (β_4) (except cash ratio in 2022). This sustained improvement reflects precautionary motives, including

reducing short-term liabilities and strengthening current assets. Common strategies included lowering inventories, accelerating accounts receivables collection, cutting expenses such as dividends and investments, and leveraging government programs such as partial employment schemes or tax deferrals. The pandemic underscored the critical role of liquidity as a buffer against unexpected shocks, prompting firms to adopt more conservative cash management practices.

After 2020, the trajectory of SGL beneficiaries diverges across liquidity ratios (β_5) compared to non-beneficiaries. In 2021 and 2022, the cash ratio declined from its initial peak but remained significantly higher for firms that received state-guaranteed loans compared to non-beneficiaries. This indicates that SGL recipients continued to have more liquidity, enabling them to cover operating costs and mitigate short-term default risk.

From 2020 to 2022, the liquidity premium for SGL beneficiaries reflects mechanical and behavioral factors. Mechanically, loan inflows increased cash holdings, particularly for firms adopting precautionary strategies such as reducing inventories, cutting expenses, and applying for maximum SGL duration. Behaviorally, beneficiaries might have been more risk-averse or exposed to demand shocks and thus maintained larger cash buffers as insurance against uncertainty. Favorable SGL terms, including low interest rates and deferred repayment, further reduced the cost of holding cash. Consequently, the cash ratio remained significantly higher for beneficiaries through 2022, underscoring its role as an indicator of immediate solvency. However, by 2023, this advantage disappeared compared to non-SGL beneficiaries and raising concerns about a potential “cash-debt scissors” effect as debt repayment continue until 2026 for most firms.

While the cash ratio remained higher for SGL beneficiaries in 2021 and 2022 compared to non-SGL beneficiaries, the differences observed in the quick and current ratios lost their significance after 2020. The gap in the cash ratio between SGL and non-SGL narrows after 2020. Cash accounts for around 22% of cash and receivables and cash accounts for around 18% of current assets. After the reduction in cash, the effect of cash may no longer be noticeable in the quick ratio and the current ratio. The quick

and current ratios do not allow us to conclude that there has been a significant change in receivables and inventories.

SGL beneficiaries appear to have primarily used SGL funds to strengthen cash reserves rather than to expand inventories or receivables. Since these ratios aggregate more than cash, correlation with immediate liquidity risk is weaker than more conservative indicator like the cash ratio, particularly under conditions of economic uncertainty.

Although the cash ratio remained significantly higher for SGL beneficiaries, the current ratio did not increase in the same way. This suggests that additional liquidity was largely held as cash. This behavior reinforces the idea that SGL primarily served as a liquidity insurance mechanism rather than as a catalyst for operational expansion.

By 2023, the liquidity gap between beneficiaries and non-beneficiaries had disappeared, despite one-third of SGL balances remaining outstanding. This decline reflects loan repayments and the redeployment of cash for post-crisis needs. As SGL repayment continues until 2026, the decline of the cash buffer raises concerns about financial resilience, highlighting the risk of a cash debt scissors effect leading to bankruptcy. These findings confirm hypotheses 1, 2, 3, and 4, highlighting the increase in liquidity of companies and more for those benefiting from state-guaranteed loans compared to those not benefiting from them, and that companies benefiting from state-guaranteed loans are more liquid during and after the crisis than before. However, hypothesis 5 is invalidated because companies benefiting from SGL are no more liquid than companies not benefiting from SGL at the end of the crisis.

INSERT TABLE 5

4.1.3. Firms default risk

Before 2020, SGL participants showed higher default risk (β_1 and β_3), compared to non-participants. Regarding the prediction of default risk scores within one year, all indicators (Altman Z and Z' score) signal an increase in default risk in 2020 for both firms that received state-guaranteed loans and those that did not (β_4). The increase was even more pronounced amongst SGL beneficiaries than among non-beneficiaries,

suggesting heightened vulnerability despite liquidity support (β_5). This validates hypotheses 6 7 and 8. This finding contrasts with the low bankruptcy rates observed in 2021. The discrepancy can largely be attributed to the liquidity support provided by SGL and other public measures, which temporarily shield firms from bankruptcy despite the deteriorating conditions.

From 2021 onward, compared to 2020, risk of default for firms reduced (β_4). Default scores remain degraded for SGL participants compared to non-participants (β_5), but not significantly. This is counter-intuitive, given that we now know 2024 experienced an abnormally high level of corporate bankruptcies.

INSERT TABLE 6

These findings on default scores show that companies benefiting from state-guaranteed loans no longer present a higher significant risk of default after the crisis than those that did not benefit from them based, thus invalidating hypothesis 9 and 10.

This disconnect highlights a key limitation of traditional risk of default scoring models: their lower ability to accurately predict extreme events (Covid-19 crisis) in the presence of exogenous policy interventions (SGL) and macroeconomic shocks. To address this limitation and better understand the predictive power of these scores, we now turn to an analysis of bankruptcy events from 2020 through 2025.

4.1.4. Firms' bankruptcy rate

Figure 3 presenting cumulative bankruptcy ratios for SGL beneficiaries and non-beneficiaries defined respectively as $\sum_{y=2020}^i \frac{N_{SGL}(\text{Bankruptcy})}{N_{SGL}}$ and $\sum_{y=2020}^i \frac{N(\text{Bankruptcy})}{N}$ shows a growing gap in bankruptcy rates for SGL firms in 2023, 2024 and 2025 compared to non-SGL firms.

This trend suggests that while SGL may have provided short-term liquidity relief until 2022, they may also have delayed but not prevented bankruptcy for financially fragile firms. The growing gap in bankruptcy rates raises concerns about the long-term

viability of SGL-supported firms and points to the need for more nuanced risk assessment tools.

INSERT FIGURE 3

These findings show that after the crisis, companies that benefited from state-guaranteed loans went bankrupt more often than those that benefited not.

4.1.5 Updated default prediction model

To further investigate the role of SGL as a determinant of default risk, we now proceed with an update of Altman Z' score, following the methodology proposed by Altman (2013), to assess the predictive power of financial indicators in distinguishing defaulting from non-defaulting firms. We performed a logistic regression with the SGL dummy variable to explain the impact of SGL on the default score.

We ran the F -test to find out if the samples of non-bankrupt and bankrupt companies had unequal variances, which they did. With that information (in Table 7 Panel A), we ran a paired samples' t -test to determine if the means of the non-bankrupt companies' ratios had statistically significant differences from those of bankrupt companies, and we found that they did. The ratios are higher for non-bankrupt firms. Only ratio 3 and 4 are statistically significant, highlighting good predictors of bankruptcy. Bankrupt firms showed medians of ratios that are larger than the means, indicating a left-skewed distribution. This is consistent with a sample where some companies experienced significant financial losses, resulting in highly negative ratios.

We obtain the following model :

$$\text{Updated Z'-Score} = -1.721X_1 - 1.048X_2 + 8.343X_3 + 2.034X_4 + 0.098X_5 - 0.293X_6$$

We computed the Z'-scores ratios and probabilities for observations of bankrupt and non-bankrupt companies. We see the models' performance metrics in Table 7 Panel B. The model presents an accuracy over 80%, which is considered as good for a logit model. F1 score is more than 90%, which signifies an excellent ability to predict negative values.

INSERT TABLE 7

The negative SGL coefficient indicates its negative role in the risk prediction model. However, the small size of the coefficient and its lack of significance suggest that SGL is not the primary cause of bankruptcy. These elements demonstrate that the SGL variable has a negative impact on firms' risk of default, thus validating hypothesis 11.

4.2.Complementary results & robustness check

To compare our TDD approach with standard methods, table 8 and 9 report results from Difference-in-Differences (DiD) estimations with and without Propensity Score Matching (PSM), following the methodology outlined in Foreau et al. (2024). Propensity Score Matching method allows studies to be conducted on non-random samples by reducing confounding bias using covariates. This is achieved by pairing companies in the smaller group (in this case, companies benefiting from state-guaranteed loans) with companies in the larger group on a one-to-one basis, according to a set of features. These analyses confirm that loan signed up was substantially higher among SGL beneficiaries than non-beneficiaries. Similarly, short-term bank debt (due within one year) was significantly greater for firms participating in the SGL program.

DiD estimates confirmed an increase in liquidity across all three ratios—cash, quick, and current—for SGL beneficiaries relative to non-beneficiaries in 2020. This significant effect remains for the cash ratio, which remains higher for beneficiaries in 2021 and 2022 under standard DiD specifications, though this significance disappears when PSM is applied. These findings suggest that the liquidity boost for SGL firms was concentrated in 2020, with subsequent trends becoming highly heterogeneous across firms and ratios.

Turning to default risk, Altman Z and Z'-score-based DiD estimates reveal a similar pattern. Default risk increased for both groups in 2020, but the rise was significantly greater among SGL beneficiaries compared to non-SGL beneficiaries. In 2021,2022 and 2023, default risk remains higher for beneficiaries under DiD but loses significance when PSM is introduced. This mirrors the liquidity results: the most pronounced divergence

between SGL participants and non-participants occurred in 2020, while post-crisis trajectories exhibit heterogeneity.

INSERT TABLE 8

INSERT TABLE 9

5. Discussion and Conclusion

This study contributes to the growing literature on state-guaranteed loans by assessing the impact of the French SGL program on corporate financial statements and default outcomes using a triple-difference methodology. We focus particularly on changes in debt levels, liquidity, and bankruptcy rate between 2020 and 2025.

Our findings reveal that firms participating in the SGL program were no more before the crisis but more liquid at the onset of the crisis compared to non-SGL beneficiaries, primarily due to increased cash holdings. These results validate hypotheses 1, 2 and 3. However, this liquidity advantage compared to non-SGL participants dissipated over the medium term, as firms began repaying their debts and may have used the funds to cover operational costs. By 2023, no significant liquidity difference remained between SGL beneficiaries and non-beneficiaries, invalidating our hypothesis 5. This means that companies benefiting from SGL are no more liquid than those that have not benefited from it, even though they still have debt to pay, which can lead to liquidity risk. However, companies in general are more liquid than before the crisis, including companies benefiting from state-guaranteed loans and may partially mitigate the liquidity risk, which validates hypothesis 4.

SGL participants showed higher default risk before 2020. Risk of default increases in 2020 for both firms that received state-guaranteed loans and those that did not. The increase was more pronounced amongst SGL beneficiaries. The medium-term Altman Z and Z' scores show no significant difference between companies benefiting from SGL and those not benefiting from it. These results based on Altman default scores validate our hypotheses 6, 7 and 8 on default risk but invalidate our hypotheses 9 and 10. The findings challenge the effectiveness of default prediction models, such as the Altman Z -

score, in crisis contexts and underscore the latent risk of zombification—where firms survive due to aid but remain financially unsustainable.

In terms of bankruptcy, while France experienced a temporary decline in bankruptcies during the early crisis years, a sharp catch-up effect occurred thereafter. SGL beneficiaries exhibited higher bankruptcy rates from 2023, with the gap widening by 2025. This trend suggests that SGL may have delayed rather than prevented bankruptcy for vulnerable firms.

Furthermore, due to the role taken by SGL in bankruptcy rate, we update Altman Z'-default score to integrate SGL treatment dummy as a discriminant variable, enhancing its relevance in post-crisis financial modeling. The negative value of SGL coefficient in the model allows us to conclude that our hypothesis 11 is valid. The surge in bankruptcy in 2024—66,121 business bankruptcies, a 17.4% year-over-year increase— and in 2025 confirms the delayed impact of the crisis and the limitations of unconditional support. The *Banque de France* (2025) attributes part of this increase to a catch-up effect following the artificially low bankruptcy rates in 2020–2021. As countries continue to grapple with the economic aftermath of COVID-19, our study offers critical insights into the unintended consequences of government support programs.

Our study sought to determine whether SGL had succeeded in fulfilling their function of ensuring liquidity and reducing risk of defaults in the medium term. Based on the data analyzed, we can say that the short-term positive impact was significant, but the medium-term results are much more mixed, with no liquidity gap between companies that benefited from SGL and those that did not, and a higher bankruptcy rate for companies that benefited from SGL.

These findings highlight the importance of setting clear eligibility criteria for loan guarantees to minimize adverse selection and moral hazard. More precise targeting

could also mitigate the risk of economic zombification, which may have been exacerbated by successive aid measures introduced since 2022, such as “resilience SGL”².

For companies that are unable to repay SGL, and to avoid numerous bankruptcies, it is important to consider the transitional measures that could be put in place. For example, the introduction of a state guaranteed loan that could be converted into state equity raises the question of which format would allow for a more efficient allocation of resources by enabling a better sharing of long-term interests and risks between the state, companies, and banks.

A promising avenue for future research would be to extend the longitudinal analysis beyond the COVID-19 period, incorporating financial statements and bankruptcy data through 2030, when all SGL-related repayments are due. This would enable a comprehensive ex-post evaluation of the long-term effects of SGL on corporate health and economic development. A key question remains: will the SGL system hinder economic growth in the long run? To explore this, future studies could examine the evolution of productivity, investment behavior, and employment dynamics among SGL beneficiaries compared to non-beneficiaries. Additionally, researchers could assess whether firms that survived due to SGL contribute meaningfully to innovation and value creation, or whether they represent a drag on economic dynamism or stability—thereby shedding light on the broader macroeconomic implications of crisis-era support policies.

² SGL “Resilience” is a government guarantee scheme for companies that are severely affected by the economic consequences of the conflict in Ukraine. Following the same model as the SGL during the COVID-19 pandemic, it is implemented in France between April 2022 and December 2023.

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Table 1: Sector and size statistics

Panel A: Sector	SGL: Participants (%)	SGL: Non- participants (%)	SGL: All (%)
C - Manufacturing	31	36	35
G – Wholesale, Retail Trade and Repair of Motor Vehicles and Motorcycles	32	28	29
F - Construction	10	11	11
M - Professional, Scientific, and Technical Activities	7	6	6
H - Transportation and Storage	3	5	5
Others	17	14	14
Total (%)	100	100	100
Total (unit)	259	1867	2126

Panel B: Size	SGL: Participants (%)	SGL: Non- participants (%)	SGL: All (%)
Large	1	2	2
Mid-Cap	34	44	42
Medium	40	39	39
Small	20	14	15
Micro	5	1	2
Total (%)	100	100	100
Total (unit)	259	1867	2126

Note: This table shows the percentage of sectors in each subsample. The sectors correspond to the ISIC Rev.4 / NACE Rev.2 / NAF Rev.2 classifications and the sizes correspond to French and European standards (see appendix 2).

Table 2: Summary statistics and correlation matrix for 2019.

Panel A									
	SGL: Participants	N	Mean	St. Dev.	Minimum	Q25%	Median	Q75%	Maximum
	Loan Signed Up / TA	259	0,03	0,08	0,00	0,00	0,00	0,02	0,52
	Bank Debt / TA	259	0,12	0,14	0,00	0,02	0,07	0,18	0,54
	Debt <1y. (>1y. at origin) / TA	259	0,02	0,04	0,00	0,00	0,01	0,03	0,25
	Cash Ratio	259	0,35	0,58	0,00	0,04	0,15	0,37	3,26
	Quick Ratio	259	2,47	4,77	0,25	0,92	1,18	1,60	32,57
	Current Ratio	259	2,89	4,68	0,72	1,22	1,52	2,38	32,57
	Altman Z score	259	2,94	1,44	0,37	1,94	2,74	3,77	7,33
	Altman Z' score	259	2,50	1,25	0,26	1,65	2,34	3,27	6,36
	SGL: Non-participants	N	Mean	St. Dev.	Minimum	Q25%	Median	Q75%	Maximum
	Loan Signed Up / TA	1867	0,02	0,05	0,00	0,00	0,00	0,00	0,33
	Bank Debt / TA	1867	0,07	0,11	0,00	0,00	0,01	0,10	0,52
	Debt <1y. (>1y. at origin) / TA	1867	0,01	0,03	0,00	0,00	0,00	0,01	0,15
	Cash Ratio	1867	0,38	0,89	0,00	0,01	0,09	0,36	6,65
	Quick Ratio	1867	1,74	2,12	0,29	0,91	1,24	1,73	16,21
	Current Ratio	1867	2,20	2,15	0,54	1,21	1,64	2,30	16,22
	Altman Z score	1867	3,08	1,54	0,08	2,04	2,95	3,90	8,59
	Altman Z' score	1867	2,63	1,33	0,19	1,76	2,54	3,31	7,87
	SGL: All	N	Mean	St. Dev.	Minimum	Q25%	Median	Q75%	Maximum
	Loan Signed Up / TA	2126	0,02	0,05	0,00	0,00	0,00	0,00	0,34
	Bank Debt / TA	2126	0,08	0,11	0,00	0,00	0,02	0,12	0,52
	Debt <1y. (>1y. at origin) / TA	2126	0,01	0,03	0,00	0,00	0,00	0,02	0,15
	Cash Ratio	2126	0,38	0,86	0,00	0,01	0,09	0,36	6,49
	Quick Ratio	2126	1,81	2,39	0,28	0,91	1,23	1,72	17,74
	Current Ratio	2126	2,26	2,40	0,55	1,21	1,63	2,31	17,78
	Altman Z score	2126	3,06	1,52	0,18	2,02	2,94	3,88	8,48
	Altman Z' score	2126	2,62	1,32	0,21	1,73	2,53	3,30	7,67
Panel B									
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	
(1)	Loan Signed Up / TA								
(2)	Bank Debt / TA	0.40 ***							
(3)	Debt <1y. (>1y. at origin) / TA	0.43 ***	0.62 ***						
(4)	Cash Ratio	0.06 ***	0.04 *	0.05 **					
(5)	Quick Ratio	0.09 ***	0.09 ***	0.04 *	0.67 ***				
(6)	Current Ratio	0.10 ***	0.12 ***	0.07 ***	0.67 ***	0.97 ***			
(7)	Altman Z score	-0.15 ***	-0.19 ***	-0.08 ***	0.18 ***	0.11 ***	0.15 ***		
(8)	Altman Z' score	-0.16 ***	-0.20 ***	-0.09 ***	0.10 ***	0.01	0.04 *	0.98 ***	

Note: This table presents the financial characteristics of the companies in each sample. In the denominator, TA corresponds to Total Assets in 2019 and TO to Turnover in 2019. Values are winsorized at the 1% level. In the correlation matrix, ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Figure 1: Triple difference-in-differences estimation

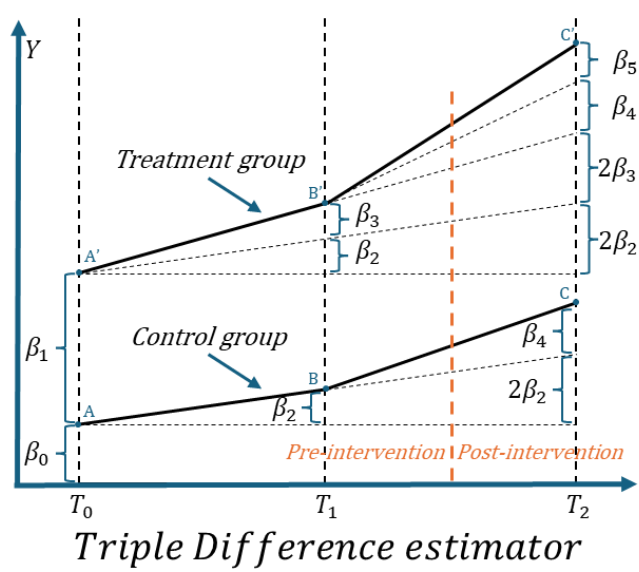
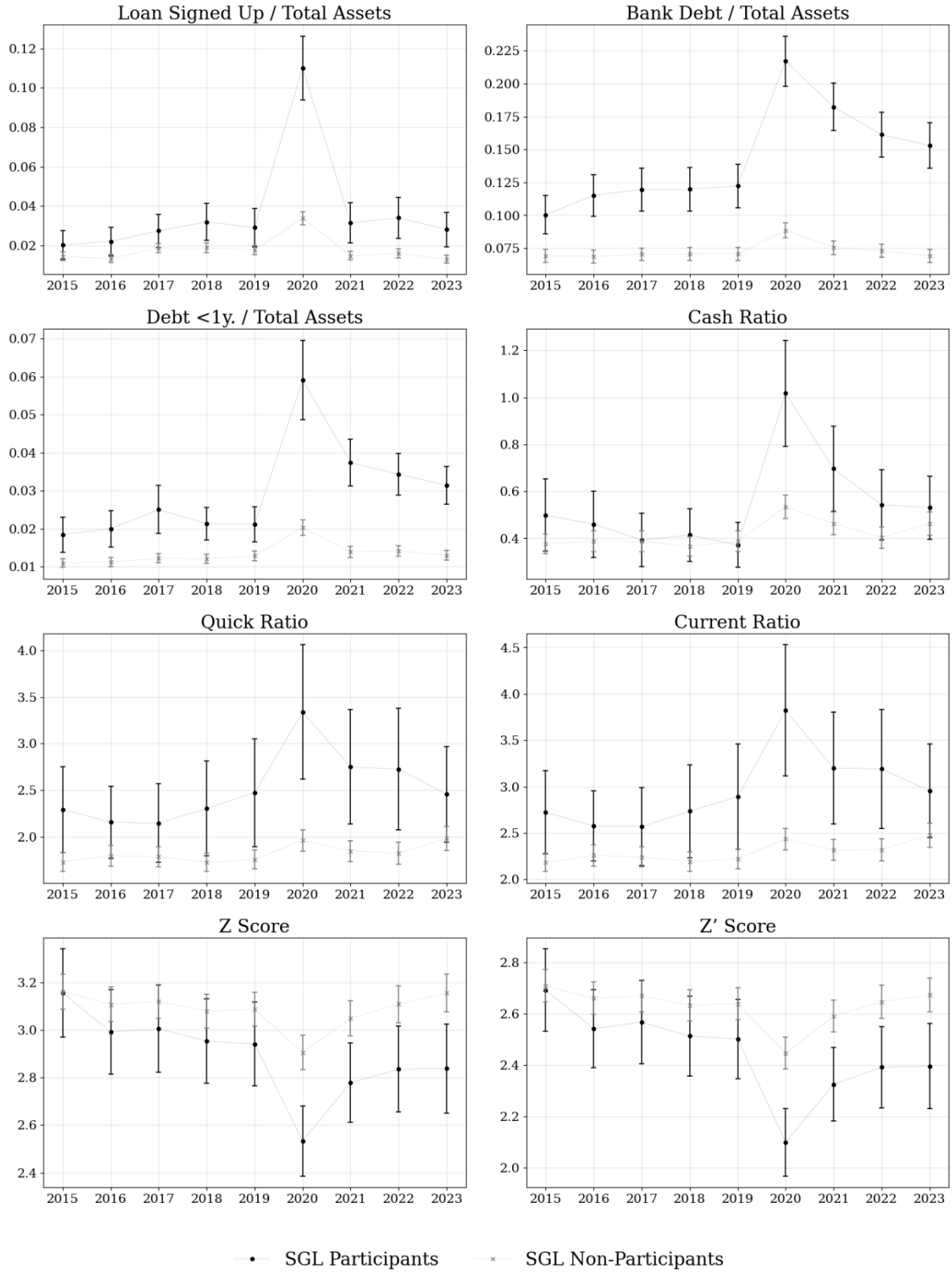


Table 3: Duration between two dates in the TDD (Year)

	1	2	3	4
T_0	2018	2017	2016	2015
T_1	2019	2019	2019	2019
T_2	2020	2021	2022	2023

Figure 2: Comparative evolution of financial ratios for firms participating in SGL versus firms not participating in SGL between 2015 and 2023



Note: This figure presents the mean values of the ratios studied in the TDD. The lines show the 95th confidence interval. Values are winsorized at the 1% level. See Appendix 3 for figure without unknown firms.

Table 4: Triple Difference-in-differences: Impact of SGL on debt

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Loan Signed Up / TA				Bank Debt / TA				Debt <1y. / TA			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.006 (0.034)	0.010 (0.026)	0.037 (0.030)	0.016 (0.028)	-0.045 (0.025)	-0.028 (0.020)	-0.026 (0.021)	-0.031 (0.024)	- 0.020*** (0.006)	-0.012* (0.005)	-0.011 (0.006)	-0.007 (0.008)
β_1	0.009* (0.004)	0.006 (0.004)	0.008* (0.003)	0.004 (0.004)	0.044*** (0.009)	0.044*** (0.008)	0.042*** (0.008)	0.027*** (0.008)	0.007*** (0.002)	0.009*** (0.002)	0.007*** (0.002)	0.005** (0.002)
β_2	-0.001 (0.001)	-0.001 (0.001)	0.005*** (0.001)	0.003* (0.001)	0.000 (0.001)	0.000 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001* (0.000)	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)
β_3	-0.003 (0.005)	0.001 (0.004)	0.000 (0.005)	0.003 (0.004)	0.002 (0.004)	0.002 (0.005)	0.004 (0.006)	0.020** (0.007)	-0.002 (0.002)	-0.003 (0.002)	-0.001 (0.002)	0.001 (0.002)
β_4	0.018*** (0.003)	-0.002 (0.002)	-0.007** (0.002)	- 0.009*** (0.002)	0.018*** (0.002)	0.005 (0.003)	-0.000 (0.003)	-0.004 (0.003)	0.009*** (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.002 (0.001)
β_5	0.068*** (0.010)	0.005 (0.009)	0.006 (0.008)	0.001 (0.008)	0.075*** (0.009)	0.053*** (0.009)	0.032** (0.010)	0.012 (0.011)	0.032*** (0.006)	0.018*** (0.004)	0.013*** (0.004)	0.010* (0.004)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378
R ²	0.090	0.035	0.031	0.032	0.111	0.093	0.083	0.080	0.082	0.069	0.071	0.065
Adjusted R ²	0.086	0.031	0.027	0.029	0.108	0.090	0.080	0.077	0.079	0.066	0.067	0.062

Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The number of observations in the regression is three times the number of firms for the difference-in-differences.

Table 5: Triple Difference-in-differences: Impact of SGL on liquidity

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Cash Ratio				Quick Ratio				Current Ratio			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.778 (0.834)	1.928 (2.116)	1.127 (1.159)	0.730 (0.803)	2.995** (1.108)	4.096 (2.229)	2.716** (0.965)	2.045** (0.700)	3.869** (1.303)	5.015 (2.687)	3.631* (1.444)	2.771*** (0.793)
β_1	-0.125* (0.056)	-0.173** (0.061)	-0.101 (0.070)	-0.060 (0.068)	-0.147 (0.132)	-0.239 (0.145)	-0.212 (0.154)	-0.030 (0.160)	-0.164 (0.140)	-0.261 (0.148)	-0.239 (0.157)	-0.035 (0.165)
β_2	0.026* (0.011)	-0.016 (0.017)	-0.016 (0.017)	0.007 (0.016)	0.057* (0.024)	-0.044 (0.035)	-0.046 (0.036)	0.038 (0.038)	0.049 (0.025)	-0.036 (0.036)	-0.045 (0.038)	0.044 (0.039)
β_3	-0.065 (0.040)	-0.006 (0.047)	-0.072 (0.063)	-0.112 (0.061)	0.111 (0.106)	0.199 (0.140)	0.156 (0.172)	0.023 (0.174)	0.094 (0.107)	0.189 (0.142)	0.150 (0.173)	-0.008 (0.177)
β_4	0.154*** (0.021)	0.114*** (0.027)	0.039 (0.026)	0.091** (0.028)	0.212*** (0.044)	0.208*** (0.063)	0.229** (0.075)	0.269*** (0.073)	0.225*** (0.045)	0.201** (0.063)	0.257*** (0.076)	0.298*** (0.075)
β_5	0.556*** (0.117)	0.234* (0.095)	0.221* (0.097)	0.183 (0.107)	0.516* (0.226)	0.027 (0.245)	0.091 (0.302)	-0.190 (0.274)	0.589** (0.227)	0.066 (0.249)	0.112 (0.303)	-0.106 (0.278)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378	6378
R ²	0.207	0.197	0.188	0.174	0.312	0.300	0.267	0.258	0.271	0.261	0.233	0.221
Adjusted R ²	0.204	0.194	0.185	0.171	0.309	0.297	0.264	0.255	0.268	0.259	0.230	0.218

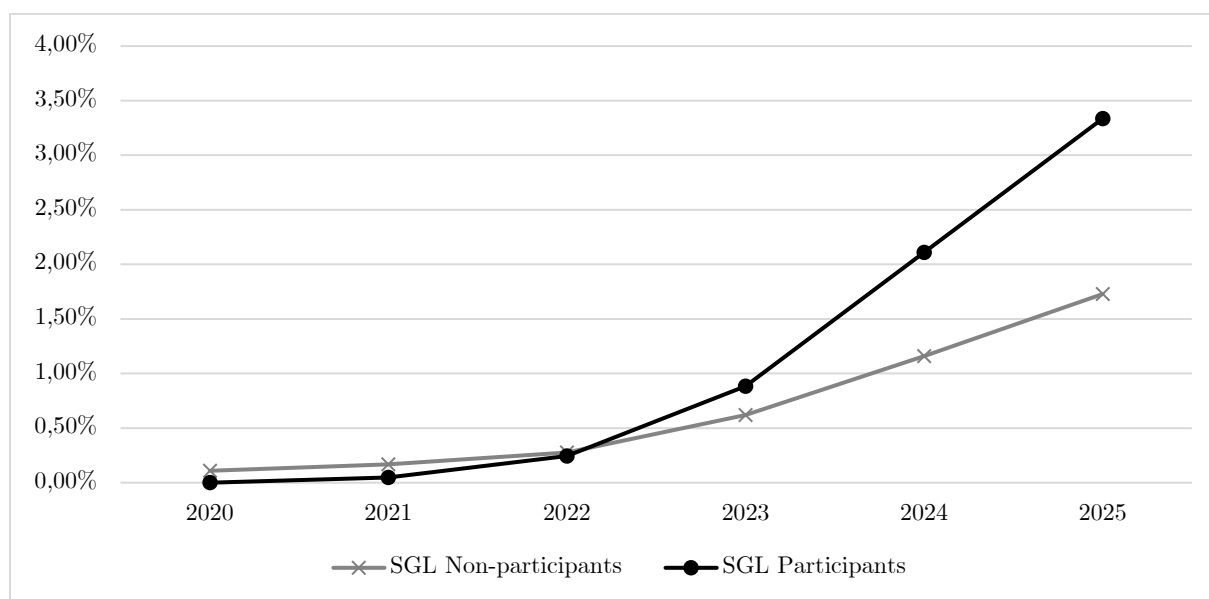
Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The number of observations in the regression is three times the number of firms for the difference-in-differences.

Table 6: Triple Difference-in-differences: Impact of SGL on default risk

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Z Score				Z' Score			
Year	2020	2021	2022	2023	2020	2021	2022	2023
β_0	3.523*	3.824**	3.582**	3.458**	2.457*	2.733**	2.492**	2.436**
	(1.456)	(1.314)	(1.329)	(1.196)	(0.965)	(0.834)	(0.868)	(0.766)
β_1	-0.258**	-0.246*	-0.261**	-0.137	-0.206**	-0.192*	-0.210*	-0.102
	(0.090)	(0.099)	(0.096)	(0.102)	(0.079)	(0.084)	(0.083)	(0.088)
β_2	0.007	-0.047*	-0.034	-0.089***	0.004	-0.036*	-0.033	-0.083***
	(0.015)	(0.020)	(0.023)	(0.025)	(0.012)	(0.016)	(0.020)	(0.021)
β_3	-0.020	-0.038	-0.033	-0.159*	-0.015	-0.033	-0.025	-0.134
	(0.047)	(0.064)	(0.070)	(0.080)	(0.043)	(0.053)	(0.062)	(0.069)
β_4	-0.185***	0.009	0.072	0.182***	-0.196***	-0.012	0.056	0.134***
	(0.026)	(0.032)	(0.038)	(0.043)	(0.023)	(0.027)	(0.033)	(0.036)
β_5	-0.211**	-0.091	-0.106	-0.025	-0.198**	-0.102	-0.106	-0.020
	(0.076)	(0.095)	(0.103)	(0.116)	(0.065)	(0.078)	(0.087)	(0.097)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6378	6378	6378	6378	6378	6378	6378	6378
R ²	0.208	0.197	0.180	0.173	0.229	0.219	0.197	0.192
Adjusted R ²	0.205	0.194	0.177	0.169	0.226	0.216	0.194	0.189

Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The number of observations in the regression is three times the number of firms for the difference-in-differences.

Figure 3: Cumulative percentage of firms bankruptcies per year



Note: This figure shows the cumulative number of firms that have gone bankrupt over time, divided by the total number of firms in the group. The graph shows that between 2020 and 2025, among the 2039 companies identified as SGL participants, 3.33% went bankrupt. Of the 237 non-participating companies that went bankrupt between 2020 and 2025, 235 companies are classified as unknown and 2 are classified as no.

Table 8: Difference-in-differences: Impact of SGL on firms following 2019.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Loan Signed Up / TA				Bank Debt / TA				Debt <1y. / TA			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.011 (0.050)	0.012 (0.028)	0.023 (0.037)	0.014 (0.027)	-0.048 (0.029)	-0.032 (0.025)	-0.040 (0.023)	-0.037 (0.020)	-0.023*** (0.007)	-0.015** (0.005)	-0.015** (0.005)	-0.012* (0.005)
β_G	0.006 (0.004)	0.008 (0.004)	0.008 (0.004)	0.008 (0.004)	0.045*** (0.009)	0.046*** (0.009)	0.046*** (0.009)	0.046*** (0.009)	0.005** (0.002)	0.006** (0.002)	0.006** (0.002)	0.006** (0.002)
β_t	0.017*** (0.002)	-0.003* (0.001)	-0.002 (0.001)	-0.005*** (0.001)	0.018*** (0.002)	0.005** (0.002)	0.002 (0.002)	-0.002 (0.002)	0.010*** (0.001)	0.002* (0.001)	0.002* (0.001)	0.000 (0.001)
β_{Gt}	0.066*** (0.008)	0.006 (0.005)	0.007 (0.005)	0.004 (0.005)	0.077*** (0.008)	0.055*** (0.008)	0.036*** (0.007)	0.032*** (0.007)	0.030*** (0.005)	0.016*** (0.003)	0.012*** (0.003)	0.011*** (0.003)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252
R ²	0.101	0.040	0.036	0.040	0.128	0.110	0.098	0.094	0.081	0.075	0.080	0.073
Adjusted R ²	0.096	0.035	0.030	0.035	0.124	0.105	0.093	0.089	0.076	0.070	0.075	0.068

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Cash Ratio				Quick Ratio				Current Ratio			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.893 (0.896)	1.513 (1.740)	1.460 (1.628)	0.980 (1.122)	3.195* (1.251)	3.162* (1.383)	2.933* (1.258)	2.296* (0.945)	4.044** (1.414)	4.193* (1.862)	4.011 (2.047)	3.061** (1.154)
β_G	-0.208*** (0.060)	-0.185** (0.057)	-0.172** (0.056)	-0.184** (0.057)	-0.089 (0.167)	-0.061 (0.166)	-0.097 (0.163)	-0.062 (0.163)	-0.118 (0.168)	-0.091 (0.167)	-0.127 (0.165)	-0.097 (0.165)
β_t	0.179*** (0.018)	0.098*** (0.017)	0.023 (0.016)	0.098*** (0.021)	0.269*** (0.036)	0.164*** (0.043)	0.183** (0.061)	0.307*** (0.059)	0.273*** (0.036)	0.165*** (0.043)	0.212*** (0.060)	0.342*** (0.061)
β_{Gt}	0.491*** (0.101)	0.228** (0.077)	0.149* (0.067)	0.071 (0.068)	0.627** (0.197)	0.226 (0.195)	0.247 (0.218)	-0.167 (0.166)	0.683*** (0.198)	0.255 (0.196)	0.262 (0.218)	-0.114 (0.171)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252	4252
R ²	0.209	0.198	0.195	0.180	0.315	0.293	0.265	0.266	0.277	0.255	0.234	0.230
Adjusted R ²	0.204	0.193	0.191	0.176	0.311	0.289	0.261	0.262	0.273	0.251	0.230	0.226

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Z Score				Z' Score			
Year	2020	2021	2022	2023	2020	2021	2022	2023
β_0	3.947* (1.660)	3.813** (1.317)	3.768** (1.460)	3.631** (1.266)	2.761* (1.078)	2.767** (0.840)	2.609** (0.918)	2.556** (0.786)
β_G	-0.277** (0.088)	-0.280** (0.088)	-0.290** (0.088)	-0.298*** (0.088)	-0.219** (0.076)	-0.223** (0.077)	-0.232** (0.076)	-0.236** (0.076)
β_t	-0.179*** (0.019)	-0.038 (0.021)	0.038 (0.026)	0.094** (0.030)	-0.193*** (0.016)	-0.049** (0.018)	0.024 (0.023)	0.051* (0.025)
β_{Gt}	-0.231*** (0.051)	-0.129* (0.060)	-0.140* (0.062)	-0.184* (0.075)	-0.213*** (0.042)	-0.135** (0.049)	-0.132** (0.050)	-0.153** (0.059)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7886	7886	7886	7886	7886	7886	7886	7886
R ²	0.208	0.204	0.184	0.175	0.230	0.225	0.201	0.194
Adjusted R ²	0.204	0.200	0.180	0.170	0.225	0.221	0.196	0.189

Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The number of observations in the regression is twice the number of firms for the difference-in-differences.

**Table 9: Difference-in-differences with propensity score matching (PSM):
Impact of SGL on firms following 2019.**

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Loan Signed Up / TA				Bank Debt / TA				Debt <1y. / TA			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.142 (0.214)	0.155 (0.186)	0.151 (0.186)	0.137 (0.162)	0.098 (0.157)	0.172 (0.132)	0.084 (0.094)	0.094 (0.099)	-0.018 (0.009)	-0.010 (0.007)	-0.008 (0.005)	-0.006 (0.005)
β_G	0.005 (0.007)	0.006 (0.007)	0.007 (0.007)	0.007 (0.006)	0.046*** (0.011)	0.047*** (0.011)	0.048*** (0.011)	0.049*** (0.011)	0.004 (0.003)	0.006* (0.003)	0.007* (0.003)	0.006* (0.003)
β_t	0.018** (0.006)	-0.007 (0.005)	-0.007 (0.004)	-0.011** (0.004)	0.022*** (0.005)	0.014* (0.005)	0.010 (0.006)	0.001 (0.005)	0.011*** (0.003)	0.001 (0.002)	0.003 (0.002)	0.002 (0.002)
β_{Gt}	0.064*** (0.010)	0.008 (0.008)	0.012 (0.007)	0.008 (0.007)	0.073*** (0.009)	0.048*** (0.009)	0.029** (0.009)	0.030*** (0.009)	0.031*** (0.007)	0.015*** (0.004)	0.010** (0.003)	0.009** (0.003)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036
R ²	0.163	0.092	0.095	0.102	0.203	0.153	0.122	0.125	0.122	0.111	0.102	0.096
Adjusted R ²	0.147	0.075	0.078	0.085	0.188	0.137	0.105	0.109	0.105	0.094	0.085	0.079

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Cash Ratio				Quick Ratio				Current Ratio			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.161 (0.255)	0.229 (0.292)	0.280 (0.265)	0.286 (0.270)	1.259* (0.605)	1.226 (0.663)	1.170* (0.530)	1.202 (0.617)	1.581** (0.492)	1.566** (0.569)	1.512** (0.458)	1.529** (0.523)
β_G	-0.240* (0.099)	-0.222* (0.097)	-0.244* (0.099)	-0.227* (0.095)	-0.239 (0.336)	-0.222 (0.336)	-0.310 (0.334)	-0.211 (0.330)	-0.297 (0.342)	-0.271 (0.342)	-0.361 (0.340)	-0.262 (0.336)
β_t	0.239*** (0.051)	0.252** (0.084)	0.185 (0.095)	0.237** (0.082)	0.216 (0.155)	0.602 (0.310)	0.417 (0.296)	0.580* (0.266)	0.255 (0.169)	0.563 (0.298)	0.398 (0.286)	0.567* (0.261)
β_{Gt}	0.500*** (0.131)	0.132 (0.128)	0.011 (0.124)	-0.070 (0.105)	0.728* (0.310)	-0.066 (0.441)	0.012 (0.390)	-0.543 (0.344)	0.779* (0.324)	0.003 (0.433)	0.076 (0.382)	-0.452 (0.341)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036	1036
R ²	0.218	0.203	0.204	0.223	0.311	0.249	0.278	0.275	0.275	0.224	0.253	0.243
Adjusted R ²	0.203	0.188	0.189	0.209	0.299	0.235	0.265	0.261	0.261	0.209	0.239	0.229

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Z Score				Z' Score			
Year	2020	2021	2022	2023	2020	2021	2022	2023
β_0	1.625*** (0.447)	1.497*** (0.425)	1.538** (0.473)	1.753*** (0.342)	1.339*** (0.396)	1.202** (0.394)	1.313*** (0.371)	1.497*** (0.246)
β_G	-0.363** (0.121)	-0.364** (0.121)	-0.376** (0.121)	-0.388** (0.121)	-0.285** (0.105)	-0.284** (0.105)	-0.294** (0.105)	-0.304** (0.105)
β_t	- (0.223***)	-0.100 (0.053)	0.001 (0.062)	0.013 (0.063)	- (0.236***)	-0.120* (0.045)	-0.018 (0.055)	-0.020 (0.058)
β_{Gt}	-0.190** (0.068)	-0.066 (0.077)	-0.106 (0.084)	-0.116 (0.091)	-0.174** (0.060)	-0.061 (0.066)	-0.096 (0.071)	-0.089 (0.079)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1036	1036	1036	1036	1036	1036	1036	1036
R ²	0.250	0.240	0.231	0.230	0.278	0.272	0.254	0.251
Adjusted R ²	0.235	0.225	0.217	0.216	0.265	0.259	0.240	0.237

Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The number of observations in the regression is twice the number of firms for the difference-in-differences.

Appendix 1 Triple difference-in-differences between the “no” and the “unknown” groups

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Loan Signed Up / TA				Bank Debt / TA				Debt <1y. / TA			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	-0.001 (0.033)	0.000 (0.024)	0.029 (0.030)	0.009 (0.027)	-0.049 (0.025)	-0.039* (0.019)	-0.029 (0.021)	-0.038 (0.024)	-0.018** (0.006)	-0.010* (0.005)	-0.010 (0.006)	-0.007 (0.008)
β_2	0.012 (0.009)	0.013 (0.010)	0.004 (0.007)	0.015 (0.009)	0.018 (0.019)	0.001 (0.016)	0.007 (0.017)	0.014 (0.017)	0.006 (0.004)	0.005 (0.005)	0.004 (0.004)	0.003 (0.004)
β_3	-0.001 (0.001)	-0.001 (0.001)	0.005*** (0.001)	0.003* (0.001)	0.000 (0.001)	-0.000 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001* (0.000)	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)
β_4	-0.005 (0.006)	-0.006 (0.008)	0.003 (0.009)	-0.007 (0.008)	0.005 (0.006)	0.022* (0.009)	0.017 (0.010)	0.009 (0.011)	0.001 (0.002)	0.002 (0.003)	0.003 (0.002)	0.004 (0.003)
β_5	0.019*** (0.003)	-0.002 (0.002)	-0.007** (0.002)	-0.009*** (0.002)	0.018*** (0.002)	0.006* (0.003)	0.001 (0.003)	-0.003 (0.003)	0.009*** (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.002 (0.001)
β_6	-0.015 (0.009)	-0.006 (0.010)	-0.006 (0.012)	0.015 (0.012)	-0.023** (0.008)	-0.039** (0.013)	-0.038** (0.014)	-0.032* (0.015)	-0.002 (0.004)	-0.005 (0.004)	-0.007* (0.003)	-0.007 (0.004)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601
R ²	0.041	0.028	0.023	0.025	0.062	0.055	0.054	0.057	0.052	0.046	0.049	0.048
Adjusted R ²	0.037	0.024	0.019	0.020	0.058	0.051	0.050	0.053	0.047	0.042	0.045	0.044

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Dependent variable:	Cash Ratio				Quick Ratio				Current Ratio			
Year	2020	2021	2022	2023	2020	2021	2022	2023	2020	2021	2022	2023
β_0	0.778 (0.830)	1.971 (2.166)	1.121 (1.150)	0.720 (0.788)	3.019** (1.127)	4.127 (2.256)	2.749** (0.985)	2.052** (0.715)	3.895** (1.314)	5.049 (2.708)	3.668* (1.452)	2.778*** (0.797)
β_2	0.173 (0.126)	0.237 (0.195)	0.066 (0.157)	-0.002 (0.137)	0.434 (0.294)	0.596 (0.399)	0.385 (0.385)	0.132 (0.301)	0.419 (0.303)	0.534 (0.400)	0.327 (0.394)	0.089 (0.304)
β_3	0.030** (0.011)	-0.014 (0.017)	-0.015 (0.017)	0.007 (0.016)	0.044 (0.023)	-0.049 (0.035)	-0.063 (0.037)	0.024 (0.036)	0.036 (0.024)	-0.045 (0.036)	-0.070 (0.039)	0.034 (0.038)
β_4	-0.091 (0.090)	-0.163 (0.135)	0.015 (0.142)	0.087 (0.123)	-0.020 (0.217)	-0.207 (0.218)	-0.011 (0.276)	0.260 (0.308)	-0.030 (0.217)	-0.170 (0.223)	0.020 (0.281)	0.275 (0.308)
β_5	0.130*** (0.020)	0.095*** (0.026)	0.033 (0.025)	0.084** (0.029)	0.204*** (0.042)	0.171** (0.056)	0.208** (0.067)	0.260*** (0.068)	0.220*** (0.043)	0.168** (0.057)	0.246*** (0.069)	0.285*** (0.070)
β_6	0.360* (0.179)	0.610* (0.303)	0.296 (0.327)	0.440 (0.254)	0.338 (0.360)	1.044 (0.709)	0.718 (0.887)	0.876 (0.853)	0.309 (0.366)	1.006 (0.713)	0.661 (0.893)	0.923 (0.879)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601
R ²	0.218	0.222	0.210	0.192	0.285	0.293	0.248	0.237	0.242	0.252	0.213	0.203
Adjusted R ²	0.215	0.219	0.206	0.188	0.281	0.290	0.245	0.234	0.238	0.249	0.210	0.199

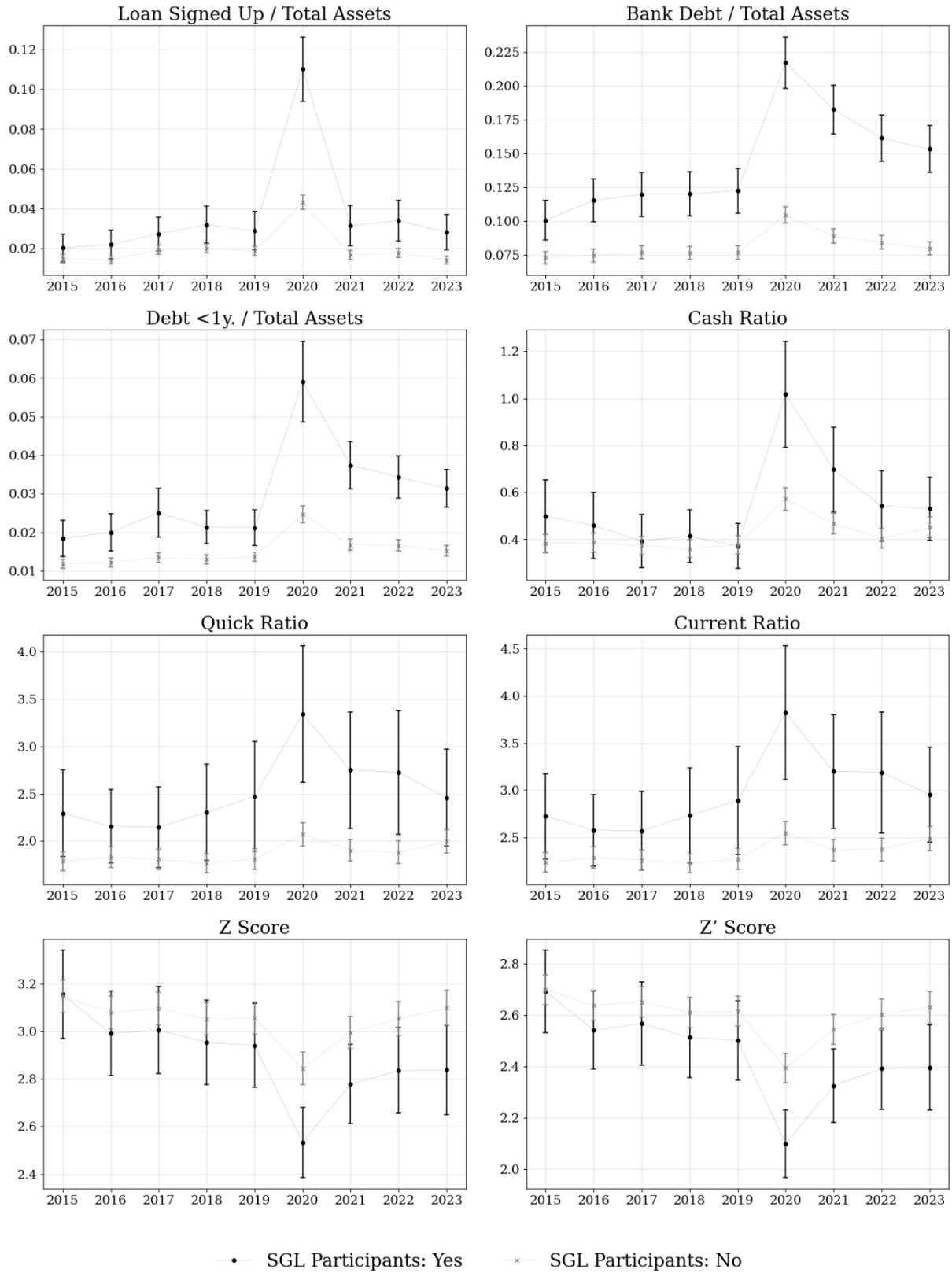
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variable:	Z Score				Z' Score			
Year	2020	2021	2022	2023	2020	2021	2022	2023
β_0	3.564* (1.446)	3.933** (1.316)	3.612** (1.322)	3.471** (1.189)	2.488** (0.959)	2.774*** (0.829)	2.519** (0.865)	2.450** (0.764)
β_2	0.349 (0.185)	0.263 (0.199)	0.370 (0.224)	0.338 (0.219)	0.262 (0.166)	0.172 (0.171)	0.275 (0.196)	0.285 (0.200)
β_3	0.007 (0.015)	-0.041* (0.020)	-0.031 (0.024)	-0.084** (0.026)	0.006 (0.013)	-0.035* (0.017)	-0.028 (0.020)	-0.077*** (0.021)
β_4	-0.052 (0.069)	0.022 (0.113)	-0.092 (0.154)	-0.062 (0.158)	-0.067 (0.057)	0.014 (0.081)	-0.095 (0.126)	-0.104 (0.145)
β_5	-0.190*** (0.027)	0.000 (0.033)	0.068 (0.039)	0.193*** (0.046)	-0.199*** (0.023)	-0.021 (0.028)	0.046 (0.034)	0.134*** (0.037)
β_6	0.173 (0.128)	0.258 (0.220)	0.382 (0.288)	0.256 (0.322)	0.152 (0.100)	0.187 (0.175)	0.298 (0.242)	0.198 (0.266)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5601	5601	5601	5601	5601	5601	5601	5601
R ²	0.210	0.202	0.179	0.166	0.228	0.222	0.195	0.187
Adjusted R ²	0.206	0.199	0.175	0.162	0.224	0.218	0.191	0.184

Note: Standard errors (in brackets) are clustered at the firm level; ***, **, and * indicate significance at the 0.1%, 1% and 5% levels. Values are winsorized at the 1% level. Fixed effect applied to size and sector. The unknown group is considered as treated group. Observations is three times the number of firms.

Appendix 2: Description of variables, size and sector groups

Variable	Description		
Loan Signed Up / Total Assets	Debt incurred during the current year divided by the sum of all assets.		
Bank Debt / Total Assets	Bank debt divided by the sum of all assets.		
Debt <1y./ Total Assets	Debt maturing in less than one year, originally taken on for more than one year, divided by the sum of all assets.		
Cash Ratio	Cash, cash equivalent and marketable securities divided by current liabilities.		
Quick Ratio	Current assets minus inventory divided by current liabilities		
Current Ratio	Current assets divided by current liabilities		
Z score	Equation to predict business failure based on a multiple discriminant analysis (Altman, 1968).		
Z' score	Equation to predict business failure based on a multiple discriminant analysis (Altman, 1993)		
All monetary variables are expressed in euro units and all variables are winsorized at the 1% level.			
The conditions used to define company size are based on staff and either turnover or total assets.			
	Maximum (<)	Maximum (≤)	Maximum (≤)
Company Size:	Staff (unit)	Turnover (m€)	Total assets (m€)
Micro	10	2	2
Small	50	10	10
Medium	250	50	43
Mid-Cap	5000	1500	2000
Large			
Classification of economic activities			
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		
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		
U	Activities of extraterritorial organisations and bodies		
The sectors correspond to the ISIC Rev.4 / NACE Rev.2 / NAF Rev.2 classifications.			

Appendix 3: Evolution of financial ratios for firms labeled as participating in SGL versus firms labeled no. We excluded the group “unknown” for which we have no information



Note: This figure presents the mean values of the ratios studied in the TDD to check the assumption of parallel trend in the pre-treatment period for each year. The lines show the 95th confidence interval. Values are winsorized at the 1% level.'