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# Access to Credit after Emerging from Corporate Bankruptcy

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## Abstract

This paper identifies the credit restrictions that small firms are facing after emerging from bankruptcy. Using the French credit register, I implement a difference-in-difference strategy that exploits staggered removal of bankruptcy flags in the form of an exogenous change in credit ratings. I focus on small and medium businesses between 2012 and 2019 and show that the flag removal leads to an increase in bank credit of 1.7%. The flag removal does not make relationship banks forget about the past bankruptcy. Instead, it removes adverse information for new banks that subsequently start lending. As a result, financially constrained firms rely less on supplier debt and increase their investment by 15%.

**JEL Classification :** G21, G24, G33, G34

**Keywords :** Corporate Bankruptcy, Debt Restructuring, Credit Rating, Bank Lending Relationship, SMEs

## 1 Introduction

Debt-restructuring procedures aim for the firm to emerge from bankruptcy as a viable business, that is with a good survival rate upon emerging from the procedure. In France, there is a low continuation rate of restructured firms. Figure 1 shows that after going through a public debt restructuring procedure, 42.7% of firms do not survive beyond four

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years. This low score may result from two phenomena. For one thing, it may be the consequence of a continuation bias inherent in the French Bankruptcy Law that favors the continuation of non-viable firms (see e.g., [Plantin et al. \(2013\)](#), [Kaiser \(1996\)](#)). For another, these low survival rates can also be explained by the indirect costs resulting from bankruptcy ([Epaulard and Zapha \(2022\)](#)). Indeed, the bad reputation of having gone bankrupt can discourage stakeholders from engaging with an otherwise viable firm. Banks, in particular, may be reluctant to lend for fear that the firm will fail again.

This paper aims to explore the extent to which bank credit restrictions explain low firm survival rates after bankruptcy. The analysis of firm recovery after bankruptcy is mainly documented for large firms in the U.S.<sup>1</sup> and hardly explores the bank credit channel. There is very little evidence on small businesses. Yet a focus on SMEs<sup>2</sup> is critical, not only because most firms that file for debt-restructuring bankruptcy procedures are small<sup>3</sup>, but also because small firms have limited access to financial markets and thus rely heavily on bank credit ([Lé and Vinas \(2022\)](#)). Among the few papers exploring the issue, [Berkowitz and White \(2004\)](#) shows that after a bankruptcy, small firms in the U.S. have restricted access to credit if they are located in a state where the owner may have homestead exemptions that allow them to file for personal bankruptcy with the firms' liabilities. More closely related to my paper, [Bonfim et al. \(2012\)](#) finds that, in Portugal and after resolving default, firms have difficulties regaining access to credit if they are small, bank dependent or if their default was severe.

In this paper, I estimate whether firms may underperform post-bankruptcy because of inefficient banking restrictions by exploring their relationship with their banks. For that purpose, I measure the causal impact of removing information about a past bankruptcy on

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<sup>1</sup>This literature usually reveals poor economic performance, see [Altman et al. \(2019\)](#)

<sup>2</sup>Small and medium-sized enterprises (SMEs) are those which, on the one hand, employ fewer than 250 people and, on the other hand, have an annual turnover not exceeding €50 million or a balance sheet total not exceeding €43 million. In addition, they include the category of microenterprises which employ fewer than 10 people and have an annual turnover or balance sheet total not exceeding €2 million—definition from <https://www.insee.fr>.

<sup>3</sup>In France, 99.95% of the bankruptcy filings are that of SMEs. See <https://www.banque-france.fr>.

SMEs' access to bank credit. In France, this information is public, but its dissemination is restricted after a few years following the bankruptcy. This paper aims to estimate (i) whether information on firms' past bankruptcy triggers bank credit restrictions, and (ii) whether the diffusion of this information and the timing of its removal are economically efficient.

In the literature, the impact of past bankruptcy information on access to bank credit has been documented as far as individuals are concerned. Notably, [Bos and Nakamura \(2014\)](#), [Han and Li \(2011\)](#), [Cohen-Cole et al. \(2009\)](#), [Musto \(2004\)](#), [Dobbie et al. \(2020\)](#), and [Saengchote and Tirapat \(2017\)](#) have studied the impact of bankruptcy flag removal on consumers' access to bank credit. In particular, [Cahn et al. \(2021\)](#) studies the removal of corporate bankruptcy flag on entrepreneurs' access to bank credit. The authors find that bankruptcy discharge leads to increased access to bank credit. Notwithstanding this literature, little research studies the bankruptcy stigma of firms rather than individuals'. Yet, this focus is critical to understanding the overall efficiency of debt-restructuring bankruptcy procedures on firms' survival and resilience.

In line with this literature, I find that the flag removal increases firms' access to bank credit. The rise in credit comes from new banks' credit supply. Firms do not repay their restructured debt with this new credit. Instead, they reduce the use of supplier debt and increase their investment. These results highlight the financial constraints and underinvestment restructured firms face in the few years following bankruptcy.<sup>4</sup> Consequently, this paper supports public policy's will to shorten the time that information about past bankruptcy is available.

My method is similar to [Dobbie et al. \(2020\)](#), as I, too, exploit the fact that the bankruptcy flag removal differs by bankruptcy type. There are two public debt-restructuring bankruptcy procedures in France: the safeguard procedure ("Sauvegarde" hereafter) and the receivership (*Redressement Judiciaire* in French, "RJ" hereafter). The

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<sup>4</sup>A limitation of this paper is that it focuses on firms that survive at least four years after bankruptcy. I therefore underestimate the impact of bank restrictions on firm survival.

information about the Sauvegarde is removed from the credit register three years after the debt-restructuring agreement. In RJ, the information is removed five years after the debt-restructuring agreement. I use this exogenous event in a difference-in-difference strategy that compares access to bank credit of Sauvegarde filing firms (the treatment group) to RJ filing firms (the control group) from four quarters before to four quarters after the Sauvegarde flag removal. I measure a causal effect under the parallel trend hypothesis, for which I provide supporting empirical evidence and extensive discussion.

In France, information on the past bankruptcy of a firm is released notably via the credit rating of the Banque de France. The "bankruptcy flag removal" corresponds to the removal of this information from the credit rating. Most SMEs in my sample are under the Banque de France rating threshold (€750K of annual turnover). It means that outside bankruptcy, they are provided with a "non-significant" (or "neutral") credit rating. During the bankruptcy procedure and in the following years, they are provided with a high-risk credit rating. After bankruptcy, the flag removal from "high-risk" to "neutral" has a statistically significant effect on firms' access to credit that grows linearly over time. Firms undergoing debt restructuring have a negative credit trend because they repay their bank debt at a 10-year horizon on average, that is, a repayment schedule of 2.5% per quarter. I find that the flag removal increases treated firms' bank credit by 1.7% compared to control firms. The rise in credit comes from new banks only. The mechanism follows: bankruptcy flag removal erases past adverse information about the firm. Despite this, relationship banks do not forget about bankruptcy. Instead, new banks that are no longer informed about the past bankruptcy start lending. The solvency constraints of banks do not explain this behavior; I find that removing the high risk associated with the poor rating does not impact banks via the capital requirements channel. The credit restrictions I measure only result from a negative reputational effect. Because of these constraints, firms relied on other funding sources, such as supplier debt. With the flag removal, firms do not increase their total leverage: the share of supplier debt decreases as

soon as bank credit supply increases. This, in turn, leads to a 15% rise in investment.

The theoretical background of this paper falls within the literature of relationship banking, where relationship banks are defined by the fact that they gather soft information on their borrowers during the lending process (Rajan (1992)). As a result, outside lenders may be reluctant to lend to a firm in a strong banking relationship due to their informational disadvantage. Empirical results are mixed. Many papers find that relationship banks provide support to their clients in financial distress, either through adjusted interest rates or collateral requirements (Schäfer (2019), Bolton et al. (2016), Berlin and Mester (1999), Peek and Rosengreen (2005), Rosenfeld (2014)). Notably, Micucci and Rossi (2017) has found that debt-restructuring of Italian SMEs is more likely with relationship banks. Other papers find opposite results: Huang et al. (2015) finds that strong banking relationship decreases the probability of debt restructuring. Li et al. (2019) shows that the share of bank loans granted by relationship banks decreases in case of distress. Salvadè et al. (2022) find that banks terminate their relationships with firms when –and long before– they approach default. More broadly, Davydenko and Franks (2008) highlights that bank adapt their relationships with firms according to the country’s regulatory environment. In particular and in response to a creditor-unfriendly bankruptcy code, banks in France require more collateral than banks in Germany or the UK to ensure recovery upon default. My results align with these last papers: I find that relationship banks decrease their credit supply to restructured firms. As a result of these credit restrictions, firms seek new banking relationships as soon as the information about their past financial distress is removed.

This paper also contributes to the empirical literature that explores the impact of external credit rating on firms’ access to credit. My results are mostly in line with the literature on SMEs’ that usually finds that small business credit score is associated to an increase in lending, notably thanks to the reduction of information costs (Berger et al. (2011), Berger et al. (2005), Frame et al. (2001)), which is more acute in small firms than

in large firms (Berger and Udell (1995)). My paper also resembles that of Cahn et al. (2022) which finds that information delivered by Banque de France’s credit rating allows bank-dependent firms to start new banking relationships. Regarding firms’ economic performance, I find that flag removal increases investment by 15% while employment and turnover are not impacted. My results are consistent with the extensive literature that focuses on the impact of credit rating on firm financing and real outcomes, although this literature focuses primarily on large firms. Studies have found that good credit ratings increase firm access to credit (Goldstein and Huang (2020), Cahn et al. (2022)). Credit ratings can also trigger change in firms’ leverage and capital structure (Kisgen (2006), Tang (2009), Sufi (2009), Faulkender and Petersen (2005)), real outcomes and investment decisions (Lemmon and Roberts (2010), Chernenko and Sunderam (2012), Harford and Uysal (2014)). Bad ratings can cause rise in the cost of debt (Almeida et al. (2017), Kliger and Sarig (2002)).

The remainder of the paper is as follows. Section 2 discusses the institutional background, Section 3 introduces the data, Section 4 describes the empirical strategy to identify the credit constraints, and Section 5 the role of relationship banks, new banks and bank’s regulatory behavior to understand the channel behind the results. Section 6 brings elements on the overall economic efficiency, and Section 7 concludes.

## 2 Institutional Background

### 2.1 Two Bankruptcy Procedures

There are two public debt-restructuring procedures in France: the Sauvegarde procedure (safeguard in English) and the RJ procedure (*Redressement Judiciaire*, receivership in English). The main difference between the two procedures is the extent of the financial difficulties that the firm faces. An insolvent firm has access to RJ, while a firm that is not insolvent but can prove that it is facing serious financial problems has access to

Sauvegarde. Apart from this difference, both procedures operate mainly in the same way (see [Kastrinou \(2009\)](#) and [Epaulard and Zapha \(2022\)](#) for in-depth comparisons).

Once the firm files for Sauvegarde or RJ, a six-month observation period (renewable twice)<sup>5</sup> starts to assess the financial situation of the firm. During this period, the judicial receiver consults the creditors and drafts a repayment plan proposal. Creditors may choose from a variety of options. They can, for example, select between a proposal for full repayment over several years or a shorter repayment plan with partial debt forgiveness (haircut). The Court is provided with the plan proposal and decides its adoption and how long it should last. The plan may be, at most, ten years (fifteen years in agricultural matters). At any time during the observation period, and in particular, if no solution is possible or new debts are created, the Court can pronounce the firm's liquidation. In RJ, the Court may also open bidding to potential buyers.

The Sauvegarde plan and the RJ plan are mostly identical<sup>6</sup>: they are both plans organizing the repayment of creditors over 10 years on average, according to (i) how much the firm owes and (ii) how much the firm can reasonably repay annually. Once the plan is approved, a commissioner is appointed to ensure the respect of the deadlines and commitments. In both procedures, the firm starts with a one-year non-payment period. Afterward, the annual payments increase gradually with a minimum of 5% required by law from the third year forward.

Empirically, [Despierre et al. \(2018\)](#) examines the repayment plans of a small sample of firms that filed in the Commercial Court of Paris between 2006 and 2015.<sup>7</sup> The detailed analysis is provided in Appendix B.2. I find that Sauvegarde and RJ repayments appear to be strictly identical. This preliminary analysis grounds the parallel trend assumption that my identification strategy requires.

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<sup>5</sup>The Pacte Law, implemented on January 1st, 2020, shortened the maximal length of the observation period in Sauvegarde to twelve months. My sample, which focuses on 2012-2019, is unaffected by this policy change.

<sup>6</sup>In practice, the Sauvegarde plan is governed by Articles L626-1 et seq. of the Commercial Code, to which the text essentially refers to the RJ plan.

<sup>7</sup>This small sample of firms is not the working sample of the paper.

## 2.2 Banque de France's Credit Rating

The Banque de France credit rating is a tool for banks accessible by subscription and is available to all investors via FIBEN, the Banque de France's information system. The European Central Bank also uses it to qualify eligible collateral. The rating serves as a standard reference to monitor the credit risk of potential borrowers; it is an assessment of the firm's ability to meet its financial obligations over a three-year horizon. Firms with a turnover of more than €750K are registered into FIBEN and provided with a rating. The rating is based on several factors: hard information comes from the analysis of the firm's accounting and financial data, the soundness of its economic environment and partners, the occurrence of events such as payment default or bankruptcy, etc. However, the rating also includes soft information; it comes from analysts in the Banque de France network who conduct interviews, extra-accounting analyses, and rigorous qualitative research to produce a firm's rating.

The rating scale contains twelve notches from P (bankruptcy) to 3++ (safest) and a thirteen notch: 0. Table 1 summarizes their description. A rating of 0 may convey various meanings. Most of the time, it means that the firm's turnover is below the minimum threshold of €750K and thus does not have a credit rating, i.e., a "non-significant" or "neutral" rating. It can also mean that the firm does not have sufficient recent accounting documentation to conduct the analysis or has documentation that analysts cannot use because of its activity (e.g., holdings, real estate, legal support firms, etc.). More importantly, a rating of 0 requires the firm to present no adverse information. A payment default or a bankruptcy procedure will trigger a rating even to firms below the €750K threshold. The rating is revised annually on receipt of firms' financial statements and whenever a significant development occurs.

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Insert [Table 1](#) here

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The Banque de France notifies firms whenever they receive a significant rating (i.e.,

other than 0). However, they are not informed when their rating is changed to 0.

### 2.2.1 Credit Rating in RJ

Whenever a firm files for RJ, the court registries automatically notify the FIBEN database. The firm is automatically assigned a credit rating of P (for bankruptcy "*procédure*"). The rating P lasts for the whole duration of the observation period, up to 18 months. The observation period ends with either a debt-restructuring agreement between the firm and its creditors or the firm's sale or liquidation. In the event of an agreement, adopting the RJ restructuring plan triggers the credit rating 6.<sup>8</sup>

The credit ratings resulting from court decisions can be described as "semi-automatic" and can be revised based on relevant evidence. In principle, rating 6 is maintained during the execution of the RJ plan. However, once the plan is adopted and following the analysis of accounting documents, the rating 6 may be replaced by a more (or less) favorable credit rating before the completion of the plan. Specifically, a firm executing an RJ plan may receive the following:

- a rating of 5 or 5+ if the criteria for the attribution of one of these ratings are met;
- a rating of 7, 8, or 9 in the presence of payment defaults.

The other ratings are not compatible with the presence of an RJ plan. If the plan fails and the firm files for liquidation, the rating changes automatically to P. Regardless of the plan's expiry date, FIBEN removes from its database the information about the existence of an RJ plan after five years if the plan has not failed in the meantime. From then, the rating evolves according to the regular analysis of the firm's financial accounts<sup>9</sup>.

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<sup>8</sup>Up to 2011, the credit rating of firms underdoing an RJ plan was 5. It was changed to 6 on January 1st, 2012, to convey better the credit risk carried by RJ filing firms. My sample, which focuses on the 2012-2019 period, is unaffected by this policy change. I exploit this policy change in the Appendix.

<sup>9</sup>Under Decree 2011-1836 of December 7th, 2011: "the opening of a Sauvegarde plan or an RJ plan [...] are subject to mentions in the Trade and Companies Register. This decree provides for the automatic removal of these mentions after three years in the event of a Sauvegarde plan or five years in the case of an RJ plan to assist firms that have proved their ability to restructure." (translated by the author)

### 2.2.2 Credit Rating in Sauvegarde

If a firm files for Sauvegarde, the court registries automatically notify the FIBEN database. The firm is automatically assigned a credit rating of 5. At the end of the observation period and in the event of a debt-restructuring agreement, the rating of 5 remains.

As for RJ, the credit rating of firms in Sauvegarde plans is "semi-automatic" and can be revised based on relevant evidence. During the execution period of the Sauvegarde plan, in principle, the credit rating of 5 is maintained. However, once the plan is adopted and following the analysis of accounting documents, the rating 5 may be replaced by a more (or less) favorable credit rating before the completion of the plan. Specifically, a firm executing a Sauvegarde plan may receive the following:

- a rating of 5+, 4, or 4+ if all the conditions for the attribution of one of these ratings are met;
- a rating of 4+ if the criteria for the attribution of a rating 3++, 3+, or 3 are met;
- a rating of 6 if the situation deteriorates further to the point that jeopardizes the implementation of the plan;
- a rating of 7, 8, or 9 in the presence of payment defaults.

If the plan fails and the firm files for RJ or liquidation, the rating changes automatically to P. Regardless of the plan's expiry date, FIBEN removes from its database the information about the existence of a Sauvegarde plan after three years<sup>10</sup> if the plan has not failed in the meantime. From then, the rating evolves according to the regular analysis of the firm's financial accounts. This exogenous rating removal provides my identification strategy.

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<sup>10</sup>See footnote 9

## 3 Data and Summary Statistics

### 3.1 Data Sources

My analysis exploits bankruptcy data from two sources: the first one is supplied by the Court registries directly into FIBEN and is used as input to set the credit rating. It includes the date of filing, the renewal of the observation period, the date of approval of a debt-restructuring plan, and the possible date of liquidation of the firm. The second source is the BODACC ("*Bulletin Officiel d'Annonces Civiles et Commerciales*"), provided by the Court registries online, in electronic form since January 2008<sup>11</sup>. The information reported by BODACC is public and provides complementary information to the judgments. Notably, it informs us about the duration of the plan.

My research then uses data from the SCR ("*Services Central des Risques*"), the French credit register. The SCR centralizes the loans granted by credit institutions, primarily banks, to each of their client firms every month. Since 2006, centralization has occurred when the total cumulative loan between a firm and a bank, regardless of the type of declaration, reaches the €25K threshold. Because of this threshold, the database is unbalanced, and the missing data are not random. A bank-firm total credit exposure may fall below the threshold and truncate the bank-firm observation from the data. The firm may or may not reappear when the credit exposure crosses the threshold again. Such attrition concerns 15% of the firms and may lead to an inaccurate estimation of the effect. In the analysis, I restrict the sample to firms I observe each quarter.

I create the dependent variables from this data source: the quarterly variation of total credit described in Section 4, and the dummy "new" equal to 1 if a firm starts a new banking relationship. To construct this variable, I examine all the previous loans of the firm since 2004. I code "new" equal to 1 if and only if the firm has never borrowed from this bank before.<sup>12</sup> In most specifications, I observe the firm-bank relationships at the

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<sup>11</sup>See <https://www.data.gouv.fr/en/datasets/bodacc/en>.

<sup>12</sup>Because of the collection threshold of €25K, the occurrence of a new banking relationship in the

bank level, not the bank’s local branch level. The bank’s local branch will be considered only when looking at the physical distance between a firm and its lenders.

## 3.2 Descriptive Statistics

I gather credit data with bankruptcy data. Given the nature of the firms I observe and their financial difficulties, it is plausible that part of them will file for liquidation during the plan. To control this attrition, I restrict the sample to firms whose plan was carried on for at least four years. To observe the firm survival on a 4-year horizon (unaffected by the 2020 health crisis), the sample focus on firms that started a plan between 2008 and 2016. In addition, I consider data from after 2012 because of the policy change concerning the credit rating in RJ<sup>13</sup>: we observe the sample firms between 2012 and 2019. Finally, I remove holdings, agricultural firms, and subsidiary firms. In the end, I follow 983 Sauvegarde and 5,082 RJ filing firms.

I provide summary statistics for the sample in Table 2. Panel A shows summary statistics of firm credit at the firm-quarter level. The average credit exposure of Sauvegarde filers is about €388K, bigger than that of RJ filers (€206K). Sauvegarde filers have, on average, slightly more banks than RJ filers (1.8 vs. 1.4, respectively). In addition, 3.8% of the Sauvegarde filing firms experience a payment default during the observation window, against 4.8% of RJ filing firms. Regarding debt composition, on average, Sauvegarde filers have more long-term debt than RJ filers (over one-year maturity).

Panel B provides statistics of the firms’ financial variables available on an annual basis. The median turnover for Sauvegarde filing firms is €676K, meaning that less than half of the treated firms of the sample are below the Banque de France rating threshold. Regarding RJ filing firms, the median turnover is €394K, so most of the control firms are below the rating threshold. The differences in other financial variables between

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data may come from the fact that the firm-bank relationship was previously existing, but the total credit exposure was below the threshold.

<sup>13</sup>See footnote 8.

Sauvegarde and RJ are small (Sauvegarde filing firms are, on average, less leveraged, have more cash and a better interest coverage ratio) and may not be significant. I perform a mean-comparison test on these variables in Section A, and I control for the heterogeneity in size between Sauvegarde and RJ filing firms with a propensity-score matching procedure as a robustness test.

Panel C shows summary statistics at the firm level. It gives us information about the restructuring plans in Sauvegarde and RJ. On median for the two procedures, plans last for 10 years (with a mean length of 9.6 years), which is the maximal length for firms that are not in the agricultural sector.

Lastly, panel D provides statistics on the firm-bank relationships. On average, the firms in the sample have been in a relationship for 4 and half years with their bank(s)<sup>14</sup>. About 75% of the firm-bank relationships I follow were already active during the bankruptcy procedure (Sauvegarde or RJ). Almost half of the firm-bank relationships are the primary relationships for Sauvegarde filing firms; it goes up to 61% for the RJ filing firms with fewer banks on average. Finally, 44% to 46% of the relationships occur in the same French department.

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Insert [Table 2](#) here

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### 3.3 Flag Removal

Before the econometric identification, let us analyze the characteristics of flag removal in Sauvegarde and RJ. Figure 2 represents the sharp drop in the credit rating of Sauvegarde and RJ filers around their flag removal. Almost 80% of Sauvegarde filers were rated 5 before the 12th quarter of their plan; this number drops to below 30% in the 13th quarter. RJ filers were 75% to be rated 6 before the 20th quarter of the plan; they are only 10%

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<sup>14</sup>Note that the French credit register I use starts in 2004, so the relationships I observe cannot exceed 18 years.

in the 21st quarter. I use the fact that RJ filers have their flag removed two years after the Sauvegarde flag removal and are unaffected at the three-year time horizon.

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Insert [Figure 2](#) here

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When I examine the detailed evolution of the credit rating of Sauvegarde filers (Figure 3), I observe that most firms are rated 0 after the flag removal. As explained in Section 2.2, the rating 0 means that the firm has a non-significant credit rating: either because its annual turnover is below the minimum threshold of €750K or because it did not provide enough accounting information. More importantly, a rating of 0 means no salient negative information on the firm. 61% of Sauvegarde filers are rated 0 following the flag removal. Only a few firms obtain a better credit rating after the cut-off point: 8% are rated 5+ or safer.

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Insert [Figure 3](#) here

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## 4 Identifying Credit Constraints

### 4.1 Credit Growth

To measure the impact of the credit rating removal on the firm's access to credit, I implement a difference-in-difference strategy based on a comparison of restructured firms in Sauvegarde with restructured firms in RJ. Firms in Sauvegarde and RJ are in a similar situation. They have started a public restructuring procedure and agreed with their creditors to renegotiate their debt over a maximum of ten years. As previously discussed, they have very similar repayment schedules. Firms in Sauvegarde have their semi-automatic credit rating being changed after three years (12th quarter of the plan), while firms in RJ have their rating changing after five years (20th quarter of the plan). This distinction is at the core of my strategy.

I am interested in credit evolution. Following [Amiti and Weinstein \(2018\)](#), I measure the percentage change in credit relative to a base period, which is preferable to a log change given my setting and the formation and termination of lending relationships. I study the change in credit at each quarter relative to the firm's average level of total credit the year before it filed for bankruptcy:

$$\Delta Credit_{i,t} = \frac{Credit_{i,t} - \overline{Credit}_{i,t=pre-bankruptcy}}{\overline{Credit}_{i,t=pre-bankruptcy}} \quad (1)$$

where  $Credit_{i,t}$  is the total amount of credit (short-term plus long-term) at quarter  $t$ , for firm  $i$  with all of its banks.  $\overline{Credit}_{i,t=pre-bankruptcy}$  is the quarterly average over all banks of the total credit of firm  $i$  the year before the procedure. As a robustness check, I also consider an alternative measure of credit: the quarterly change of credit<sup>15</sup>.

I compare the credit variation of restructured firms in Sauvegarde (the treatment group) with that of restructured firms in RJ (the control group) four quarters before and four quarters after the flag removal. I estimate a difference-in-difference equation:

$$\Delta Credit_{i,t} = \alpha Post_q + \beta(Post_q \times Treated_i) + \gamma_i + \gamma_{s \times t} + \epsilon_{i,t} \quad (2)$$

where  $i$  indexes the firm,  $t$  the calendar quarter,  $q$  the quarter of the plan, and  $s$  the industry.  $Post_q$  is a dummy that equals 1 when the firm's plan is older than three years.  $Treated_i$  equals 1 for Sauvegarde filers and 0 for RJ filers.  $\beta$  is the variable of interest that measures the divergence in the evolution of the dependent variable between the Sauvegarde filers and the RJ filers. I control for firm  $\gamma_i$  and industry  $\times$  quarter fixed effects  $\gamma_{s \times t}$ . To avoid serial correlation, I cluster standard errors at the firm level.

Alternatively, I conduct the dynamic analysis at the quarter level:

$$\Delta Credit_{i,t} = \sum_{q \neq 12} \alpha_q \mathbb{1}_q + \sum_{q \neq 12} \beta_q (\mathbb{1}_q \times Treated_i) + \gamma_i + \gamma_{s \times t} + \epsilon_{i,t} \quad (3)$$

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<sup>15</sup>  $alt.\Delta Credit = \frac{Credit_{i,t} - Credit_{i,t-1}}{Credit_{i,t-1}}$

where  $\mathbb{1}_q$  is a dummy for each quarter of the plan. I omit the period of the flag removal  $\beta_q = 12$  so that the other  $\beta_q$  can be interpreted relative to this baseline period. It is expected that  $\beta_q$  is not significantly different from 0 for  $q < 12$  to support the parallel trend hypothesis. If it is verified, then  $\beta_q$  for  $q > 12$  captures the causal effect of the exogenous flag removal in  $q$ .

## 4.2 Parallel Trend Hypothesis

The main identification assumption requires that credit trends of the treatment and control groups would have been identical in the absence of the flag removal. Figure 4 shows the raw quarterly average credit variation for treated and control firms. From the visual analysis, we can see that the pre-treatment trends are strictly similar for both groups. Credit decreases as firms execute their restructuring plan and repay their debt. The repayment schedule follows a regular rhythm. On average, Sauvegarde and RJ filers have repaid 26.4% of their debt after three years, or a repayment schedule of about 9.5% per year, or 2.4% per quarter. After the flag removal, a slight divergence in credit variation seems to have happened between treated and control firms from the 13th quarter onward. An econometric analysis is necessary to measure the impact of the flag removal.

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Insert [Figure 4](#) here

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Additional discussion about the validity of the parallel trends assumption can be found in Appendix [B.2](#).

## 4.3 Results

The result of estimation 2 is presented in Table 3 column (1). The coefficient  $\beta$  is positive and significant at 1% level, meaning that treated firms experience a 1.7% increase in credit relative to the control firm on average in the year following the flag removal. Interestingly,

firms repay their debt at roughly 2.5% per quarter on average: they do not increase their total leverage and continue repaying their debt but at a slower rate.

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Insert [Table 3](#) here

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Results of estimation [3](#) are reported in [Table 3](#) column (2). The coefficient estimated for quarter  $q$  correspond to the difference of evolution between the outcomes for Sauvegarde and RJ filers four quarters before the flag removal to four quarters after it. The point estimates  $\beta_q$  indicate that the total credit of Sauvegarde filers increases substantially compared to RJ filers for  $q \geq 13$ . For  $q < 12$ , the point estimates are non-significantly different from 0, meaning that there is no systemic relationship between the age of the plan and the credit variation in the pre-removal quarters. These results provide support for the parallel trends assumption. [Figure 5](#) offers a visual representation of the coefficients estimates  $\beta_q$ . The figure illustrates that the flag removal effect grows stronger with time, from 0.9% to 2%.

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Insert [Figure 5](#) here

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In recent years, extensive literature has addressed the drawbacks of the difference-in-difference approach using two-way fixed effects linear regression with more than two periods. I provide robustness tests in [Appendix B](#) that prove that the results are robust to the introduction of time, group, and cohort heterogeneity.

## 5 The Role of Banks

How can we explain the credit increase caused by the flag removal? This section aims at exploring banks' reactions to bankruptcy flag removal.

## 5.1 Intensive margin: Relationship banks

### 5.1.1 Depth of banking relationships

I first want to study the reaction of relationship banks to the bankruptcy flag removal. I want to test if the flag removal provides them with new information that could trigger a change in their behavior. To do so, I discriminate between them according to their level of information. Relationship lending is characterized by the collection of soft, proprietary information by the bank about their borrowers. One cannot observe directly the existence of such relationships; the empirical literature on relationship banking has relied on indirect, data-driven measures to infer their existence (see e.g. [Degryse and Ongena \(2008\)](#), [Harhoff and Körting \(1998\)](#), [Petersen and Rajan \(1994\)](#)). Following this literature, I consider several measures of information:

**The duration of the bank-firm relationship** serves as a first proxy for the level of information ([Berger and Udell \(1995\)](#)). The longer the relationship, the more informed the lender is about the borrower's financial situation, their ability to repay their past loans, and the viability of their business. In my set-up, I consider the lenders informed as soon as they were present during the bankruptcy procedure and thus know the details of the procedure. I define the less informed lenders with a dummy equal to one if the bank was not yet lending at the time of the bankruptcy filing and zero if it was.

**The bank is the firm's main lender.** The story behind a strong relationship is twofold. On the one hand, the firm may choose to concentrate its borrowing with a lender to reduce the monitoring cost, improve the lenders' information about its business and thus reduce the cost of borrowing ([Petersen and Rajan \(1994\)](#)). On the other hand, the bank may benefit from an informational advantage over the firm that may lead to an informational monopoly and a hold-up problem ([Cahn et al. \(2022\)](#)). In both cases, the main lender detains more information about the firm than other lenders. I define the main lender if the bank is having the largest share of bank credit in the firm's total credit.

The dummy for less informed lenders equals one for all other banks lending to the firm; they are considered "secondary."

**Informational distance** between the lender and the borrower serves as a proxy for high monitoring costs. The higher the physical distance between a firm and its banks, and the more difficult it is for the bank to gather soft information (Bolton et al. (2016), Agarwal and Hauswald (2010), Degryse and Ongena (2005), DeYoung et al. (2008)). I define the less informed lenders with a dummy equal to one if the banks' local branch and the firms' headquarters are not in the same French department, zero otherwise.

Considering the measures for information listed above, I want to question whether the less informed lenders are more likely to react to bankruptcy flag removal. I add the dummy  $D_{i,b,t}$  equal to 1 when the bank is less informed to a triple interaction term in the baseline equation:

$$\begin{aligned} \Delta Credit_{i,b,t} = & \beta_0 Post_q + \beta_1 (Post_q \times Treated_i) \\ & + \beta_2 D_{i,b,t} + \beta_3 (D_{i,b,t} \times Treated_i) + \beta_4 (D_{i,b,t} \times Post_q) \\ & + \beta_5 (Post_q \times Treated_i \times D_{i,b,t}) \\ & + \gamma_i + \gamma_b + \gamma_{s \times t} + \epsilon_{i,b,t} \end{aligned} \quad (4)$$

I run this specification at the firm-bank level,  $\gamma_b$  denotes bank fixed effects. Here, the coefficient  $\beta_5$  captures the differential impact that the flag removal has on less informed banks. If relationship banks draw positive information from restructured firms' change in rating from "0" to "5", one would expect the less informed lenders to increase their credit supply more than most informed lenders, and  $\beta_5$  to be positive.

Table 5 presents the result of equation (4) with each different columns accounting for a different measures of information. All columns point to the same result. While the effect of the flag removal is robust, the triple interaction term coefficient  $\beta_5$  is not significantly different from zero in any specification: the less informationally powerful lenders do not adjust their credit supply after the flag removal. It seems like they do not

extract positive information from the change in credit rating.

Interestingly, we notice that  $\beta_2$  is significantly negative at the 1% confidence level in columns (1) and (2). It means less informed relationship banks lend from 8% to 28% less to the restructured firm than the most informed lenders. Also,  $\beta_4$  is strictly positive: it informs us that this trend is changing over time. Less informed banks lend about 4% more credit in the fourth year after bankruptcy compared to the second year to all restructured firms. These results highlight an interesting phenomenon described by [Salvadè et al. \(2022\)](#): banks with long-standing relationship chooses to terminate lending relationships with fragile borrowers at the expense of less informed banks. Although the authors prove this phenomenon to be true before bankruptcy, [Table 5](#) suggests that most informed lenders continue transferring their fragile lending relationships to less informed lenders even after the firms' bankruptcy.

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Insert [Table 5](#) here

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In unreported results, I also measure the level of information with continuous variables. For the age of the relationship, I account for the non-linearity of an additional year of connection by controlling for the log of the age to allow the marginal impact of age to decline. Similarly, to measure whether the bank is the firm's main lender, I measure the level of information by the number of banks with which the borrower has loan business, with the idea that multiple sourcing weakens relationships and, thus, the level of information. Finally, I measure the physical distance by the log of the distance (in kilometers) between the banks' local branches and the firms' headquarters. The unreported results follow the same conclusion as in [Table 5](#): the less informed banks do not adjust their credit supply after the flag removal.

### 5.1.2 Banks' regulatory behavior

The credit rating is an assessment of the credit risk carried by the borrower. In this section, I want to test if flag removal impacts banks' behavior through the capital requirements channel. The idea behind this channel covers two possibilities:

The first possibility comes from the fact that banks can declare the credit risk of their borrowers based on their internal monitoring system, or on external credit rating as the Banque de France's<sup>16</sup>. In this set-up, the flag removal can be a positive shock that alleviates banks' capital requirements as their borrowers suddenly become risk-free according to the Banque de France credit rating.

The second possibility concerns guidelines that may shape banks' lending behavior. Independently from the actual financial situation of the borrower, banks – and in particular local branches, far from the banks' headquarters that decide on the guidelines – may be constrained to follow rules that prohibit them from lending to firms poorly rated by external rating agencies. As previously, the flag removal could make it possible to lend to the firm again.

In both scenarios, I would expect the flag removal to positively impact banks that are the most financially constrained. Note that the change in rating would not bring any new information to the lenders, but instead relieve them from financial or regulatory constraints. The following aims at testing this hypothesis.

To test the impact of the flag removal on bank credit supply via the solvency channel, I gather data from the European Banking Authority (EBA) Transparency Exercise<sup>17</sup> on the Tier 1 ratio of the main French banking groups. The Tier 1 solvency ratios divide the bank's Tier 1 capital by its risk-weighted assets. The EBA information is available for 62% of all the banks, which represents 75% of the firms in the sample. I measure the Tier 1 ratio quarterly deviation from the EU average for each bank. I then calculate

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<sup>16</sup>See Methods of calculating of prudential ratios under the CRDIV, <https://acpr.banque-france.fr/>

<sup>17</sup>See <https://www.eba.europa.eu/>.

the lagged weighted average of the banks' ratio at the firm level. I finally create the dummy  $Low_{i,t-1} = 1$  if the lagged weighted average of the firm's banks' Tier 1 ratios is in the lower quartile of the distribution.  $Low_{i,t-1} = 1$  means that the firm's banks are more constrained than the average. I add this dummy in a triple interaction term in the baseline equation:

$$\begin{aligned} \Delta Credit_{i,t} = & \beta_0 Post_q + \beta_1 (Post_q \times Treated_i) \\ & + \beta_2 Low_{i,t-1} + \beta_3 (Low_{i,t-1} \times Treated_i) + \beta_4 (Low_{i,t-1} \times Post_q) \quad (5) \\ & + \beta_5 (Post_q \times Treated_i \times Low_{i,t-1}) + \gamma_i + \gamma_{s \times t} + \epsilon_{i,t} \end{aligned}$$

In this specification,  $\beta_5$  captures the differential effect that the flag removal has on constrained banks from a solvency perspective. If banks adjust their regulatory behavior according to the Banque de France's credit rating, or if banks rely on Banque de France's external credit rating to declare the risk carried by their borrowers, one would expect the flag removal to relieve banks with low solvency more than the average, and  $\beta_5$  to be positive.

Table 6 presents the estimation results. Columns (1) and (2) present the result of equation 5 at the firm level, with and without the triple interaction term. Columns (3) and (4) present the same specification but at the bank level, with bank fixed effects. We first note that  $\beta_1$ , the difference-in-difference coefficient estimate, is robust to these alternate specifications. The coefficient  $\beta_2$  associated with the dummy  $Low_{i,t-1}$  is rather negative, meaning that firms which banks are constrained have less credit on average, but the coefficient is not always significantly different from 0. Most importantly, in columns (2) and (4), we read that  $\beta_5$  is not different from 0. Solvency constraints do not explain the credit supply after the flag removal.

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Insert [Table 6](#) here

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Although it is difficult to conclude on the absence of effect, this first analysis leads us to

believe that banks do not use Banque de France's credit rating to manage the risk of their borrowers. The first reason may be that most of the time, banks base their declaration on their internal rating, and restructured firms are always classified as "doubtful" or even "compromise" until the plan successfully comes to an end<sup>18</sup>. Relationship banks do not seem to draw soft regulatory information from Banque de France's credit rating on SMEs. Additional evidence in Appendix C reveals that banks are not impacted by an exogenous downgrade of restructured firms' external credit rating either.

Since the increase in credit does not come from relationship banks, the next section will be devoted to studying the behavior of new banks.

## 5.2 Extensive margin: New banks

I now want to estimate the impact of flag removal on the probability that a firm starts borrowing from a new bank. Following [Gopalan et al. \(2011\)](#), I estimate panel logit regression that are variants of the form:

$$P(New_{i,q} = 1) = \alpha Post_q + \beta(Post_q \times Treated_i) + \gamma_i + \gamma_t + \epsilon_{i,t} \quad (6)$$

where  $New_{i,q}$  is a dummy variable that equals 1 before  $q = 12$  if the firm starts borrowing from a new bank before  $q = 12$ , 0 otherwise; and equals 1 after  $q = 12$  if the firm starts borrowing from a new bank after  $q = 12$ , 0 otherwise.

In a first specification, I estimate a conditional logit regression that includes firm and quarter fixed effects  $\gamma_i$  and  $\gamma_t$ . The panel logit regression is estimated only on observations for which the dependent variable varies within the period of consideration. It means that the model focuses only on firms that start a new banking relationship from four

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<sup>18</sup>Anecdotal evidence collected through an interview with the restructuring department direction of a major French bank. Whenever a firm files for bankruptcy (RJ or liquidation), the bank must register the loans for which it will likely not receive all or part of the amounts due as doubtful or compromised loans. In the event of a Sauvegarde procedure, the bank must assess whether there are grounds for declaring loans as doubtful or compromised or not. In practice, such loans are almost always reported as doubtful.

quarters before to four quarters after the flag removal. However, forming a new banking relationship is rare, and limiting the sample to those firms is very restrictive. For this reason, I also estimate a panel logit regression with no firm fixed effect but with additional controls at the firm level: length of the plan, the firm’s size measured with the log of its total assets, the ratios of long term credit over total credit, and leverage (total debt/ total asset). The financial information is available only for part of the total sample, leading to a loss of observations.

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Insert [Table 4](#) here

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Table 4 presents the results of equation 6 for the logit model in columns (1) and (2) and ordinary least squares in columns (3) and (4). I find in column (3) that the flag removal increases the probability of forming a new bank relationship by 1.86 percentage points. This effect is substantial given that the unconditional propensity of starting a new banking relationship at a given quarter for Sauvegarde filers is 2.6%. Logit and OLS results are consistent. In the literature, [Cahn et al. \(2022\)](#) finds that a rating surprise for healthy and well-rated firms leads to a greater probability of starting a new banking relationship of 4% (with a quarterly probability of starting a bank relationship of 6% on average).

In a second test, I want to measure the role of new banks in the firms’ total credit supply. I split the credit between relationship banks and new banks with the following dependent variables:

$$\Delta NewCredit_{i,t} = \frac{NewCredit_{i,t} - \overline{Credit}_{i,t=pre-bankruptcy}}{\overline{Credit}_{i,t=pre-bankruptcy}} \quad (7)$$

and

$$\Delta RelationshipCredit_{i,t} = \frac{Credit_{i,t} - NewCredit_{i,t} - \overline{Credit}_{i,t=pre-bankruptcy}}{\overline{Credit}_{i,t=pre-bankruptcy}} \quad (8)$$

where  $NewCredit_{i,t}$  is the credit borrowed from new lenders. Here, a lender is considered new from quarter  $t$  forward if the firm starts borrowing from it at quarter  $t$  and has never borrowed from it before.<sup>19</sup> I then run equation 3 on these subsets of credit, results are depicted in Figures 6 and 7. Credit from relationship banks does not significantly increase after the flag removal, while credit from new banks increases significantly by 0.65% in quarter 13, up to 2.6% in quarter 16. These figures show that the formation of new banking relationships exclusively explains the credit rise after the flag removal. We also note that firms do not repay their relationship banks with the new credit: the coefficients  $\beta_q$  represented Figure 6 are not negative.

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Insert [Figure 6](#) here

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Insert [Figure 7](#) here

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These results point out that firms were financially constrained by their relationship banks. The flag removal helps them alleviate these constraints by allowing for new banking relationships. The new relationships are not the result of a change in the regulatory behavior of banks, as demonstrated in the previous sections. Banks use the external credit rating of the Banque de France to screen potential borrowers and reduce monitoring costs. It seems that until the flag is removed, firms cannot borrow from new banks because the poor rating resulting from the bankruptcy flag scared off potential lenders. The removal of adverse information weakens the stigma and reduces credit supply constraints. This is true even though the information about past bankruptcies is public and remains available after the flag removal. One possible explanation is that since firms are small, monitoring is less thorough, and new banks do not screen them beyond the credit rating.

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<sup>19</sup>I examine all the previous loans of the firm since 2004. I consider the firm-bank relationship at the bank level, not at the local branch level.

## 6 Effects of the Flag Removal on Firms Performance

### 6.1 Impact on Firms' Financial and Economic Outcomes

Is the flag removal economically efficient? The policy choice between revealing or removing information about past bankruptcies depends on its underlying economic efficiency. Increased economic performance of restructured firms after the flag removal would reveal inefficient financial constraints that should be tackled by removing the bankruptcy flag earlier. Conversely, if restructured firms perform worse once their access to credit is facilitated, it would suggest an inherent fragility that makes lending to these firms inefficient. Their past bankruptcy would then remain a piece of relevant information to deliver to banks.

To test for this, I perform a two periods difference-in-difference estimation on firms' financial and economic outcomes. Firms' financial information is available annually; therefore, I consider the year before and after the flag removal and control for year  $\times$  industry fixed effects. Financial information is not available for all of the firms, I perform this test on about two third of the main sample.

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Insert [Table 7](#) here

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Table 7 presents the results. The top panel presents the financial outcomes: the flag removal does not impact the apparent cost of debt nor the interest coverage ratio: both variables are close to zero and non-significant. With the flag removal, the supply constraints that firms face are impacted in terms of quantity, not the price of debt. Total leverage is not impacted despite the rise in bank credit; the overall debt level of treated firms does not increase. Column (4) shows that the share of supplier debt over total debt decreases significantly by 1 percentage point. It means that the mix of debt has changed, and treated firms trade about 4% of their supplier debt for bank debt.

Regarding the real economic outcomes, the bottom panel of Table 7, column (1) shows that the investment of treated firms significantly increases by 4.7 percentage points, corresponding to a rise of 15%. With no increase in leverage, it can be inferred that investment is made possible by substituting funding sources for long-term financing. Furthermore, I do not find any effect of the flag removal on turnover or employment; coefficient estimates are relatively small and not significantly different from zero. That is, the situation of the firms does not deteriorate. Lastly, results in Table 8 show that the impact of the flag removal on the occurrence of payment default is negative, although not statistically different from zero.

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Insert [Table 8](#) here

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These results indicate that firms are financially constrained and under-invest in the first few years following a debt-restructuring agreement. They overcome bank credit restrictions by relying on supplier credit, which is unsuitable for investment. Their economic situation does not worsen when they gain increased access to bank credit: they seem viable enough for the flag to be removed earlier. As such, easing the bankruptcy stigma would probably favor their survival.

## 6.2 External Validity

An inherent limit of my identification lies in that I measure the impact of the flag removal on firms that have survived at least four years after restructuring. As a result, I exclude all firms liquidated within these four years, possibly because of their credit constraints. My results are likely to be minimized because of that.

In addition, my study may suffer from potential selection bias. On the one hand, it is plausible that firms that survive four years after the adoption of the plan have unobservable characteristics affecting their access to bank credit. This possibility should be taken into account before extending the results to the entire universe of distressed firms

filing for a debt restructuring procedure. On the other hand, it is necessary to keep in mind that the banks that lend following flag removal may present specific characteristics as well. They may only be banks that would not check the quality of their borrowers beyond the Banque de France credit rating, for example.

## 7 Conclusion

The Banque de France designs the credit rating as a mix of hard and soft information (balance sheet and accounting data on the one side, interviews and expertise of Banque de France’s analysts on the other). It aims to reduce the asymmetry of information between lenders about a firm’s repayment capabilities. In this paper’s set-up, the rating provided to firms after a bankruptcy is a semi-automatic rating born out of hard information (the occurrence of a bankruptcy procedure). In my results, I do not find that the change in rating triggers a reaction among relationship banks that are aware of the past bankruptcy, or at least of the bankruptcy-induced rating.<sup>20</sup> On the contrary, the flag removal and, thereof, the removal of hard adverse information about the occurrence of a past bankruptcy impact potential lenders. The credit rating serves as reference for lenders to monitor potential borrowers ; the high-risk credit rating associated with bankruptcy deters them from lending. Since new banks do not have access to past ratings, the flag removal signals firms as having no salient information although the information about the past bankruptcy is available elsewhere for free. New banks that increases their lending do not seem to make the small effort to collect it. One possibility is that because the firms are small, monitoring is less thorough. This behavior does not result from regulatory constraints that would make them prohibitively deny credit to firms with high-risk credit

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<sup>20</sup>My result is different than in [Cahn et al. \(2022\)](#) where a positive rating surprise triggers an increase in relationship-bank credit supply. The difference is that in [Cahn et al. \(2022\)](#), the rating surprise provides soft information, while in my set-up, the flag removal provides hard information only.

ratings.<sup>21</sup> The flag removal is independent of the firms' fundamentals, therefore their improved access to bank credit and investment rise can only result from the reduction of the stigma effect associated with their past bankruptcy.

In the wake of the 2020 health crisis, many firms – otherwise viable – have suffered from fluctuating business conditions and have needed government support, notably facilitated publicly guaranteed loans, to keep their business afloat. According to [Demmou et al. \(2021\)](#), about 8% of all firms may be threatened by debt overhang and require debt restructuring. In this context, alleviating financial constraints faced by firms after financial distress has become a priority. Public authorities have taken measures to improve their refunding conditions and support the economic rebound. In France, the flag removal that occurred after three years in the Sauvegarde plan and five years in the RJ plan has been reduced to 2 years in 2020 for both procedures.<sup>22</sup> Also, a "post-money" privilege<sup>23</sup> has been introduced to encourage banks to lend to restructured firms by guaranteeing a preferential ranking of lenders that refund firms in Sauvegarde and RJ plan. These measures specifically aim at encouraging and facilitating the credit access of restructured firms to help their recovery.

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<sup>21</sup>[Cahn et al. \(2021\)](#) show that when the information about entrepreneurs' past bankruptcy is available at a small cost, banks do not seek it out.

<sup>22</sup>Decree N-2020-106 of February 10, 2020.

<sup>23</sup>Order no. 2020-596 of May 20th, 2020, extended by Order no. 2021-1193 of September 15th, 2021.

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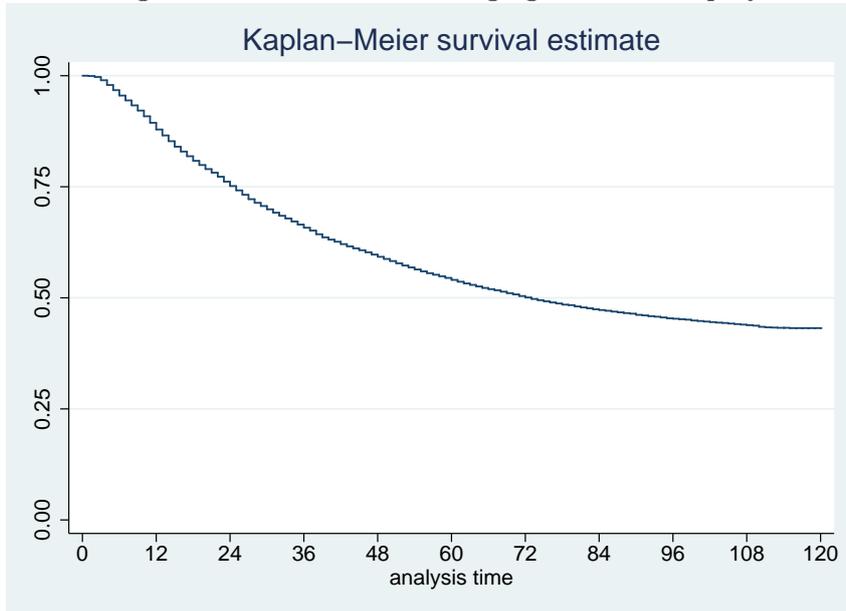
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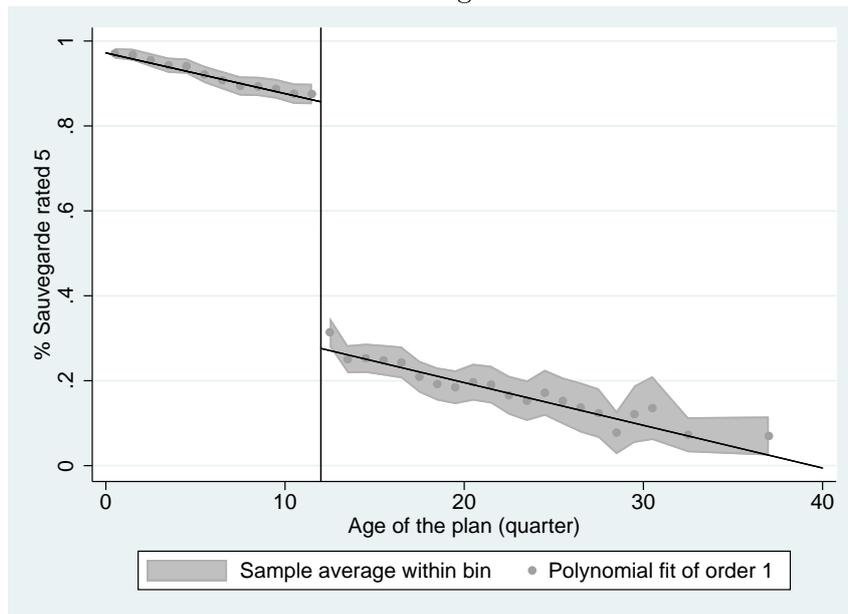
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Figure 1: Survival after Emerging from bankruptcy

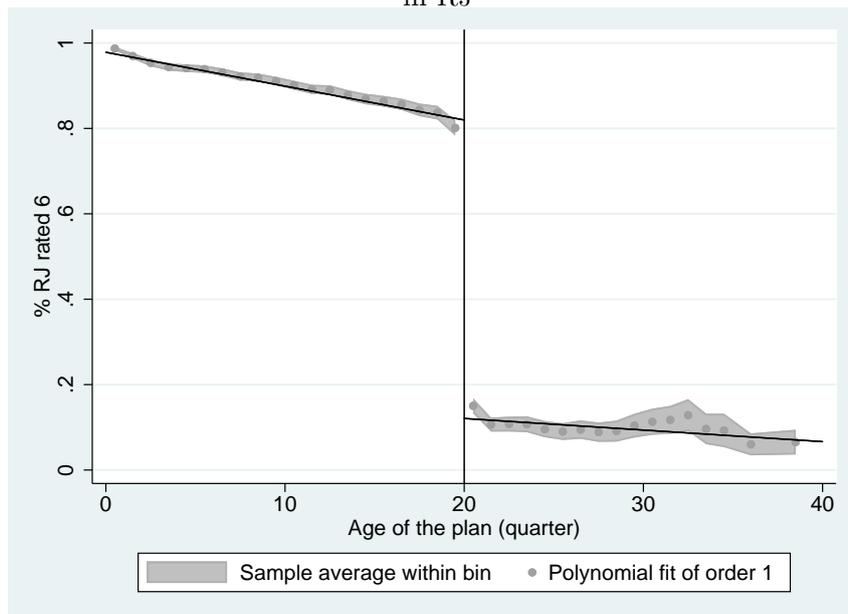


**Note:** Analysis time define in months since the beginning of the debt-restructuring plan. The survivor estimate is defined as the probability of not falling back to bankruptcy. Sample includes 47,555 firms filing for a debt-restructuring bankruptcy procedure in France between 2004 and 2021.

Figure 2: Credit rating of firms in continuation plan  
in Sauvegarde

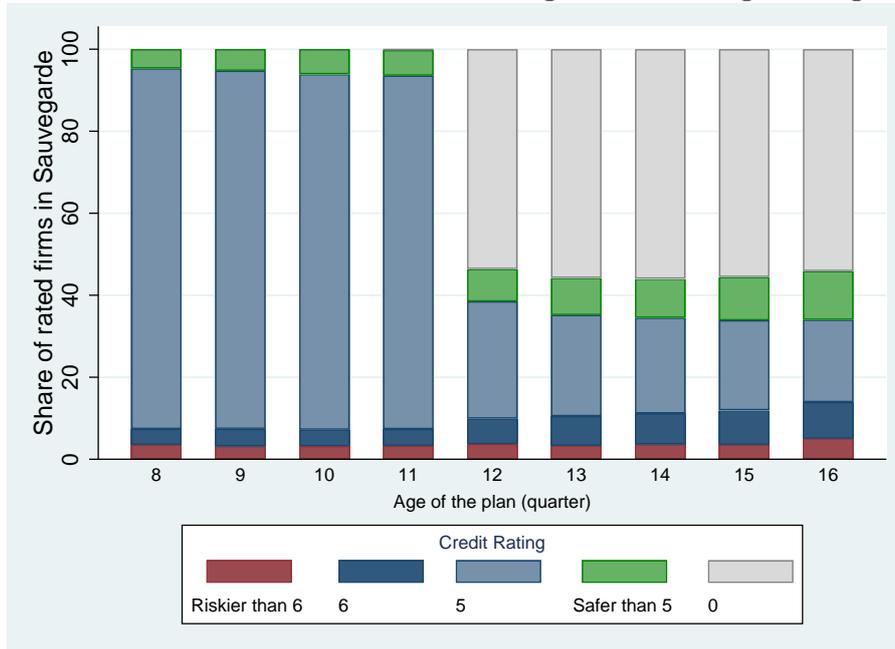


in RJ



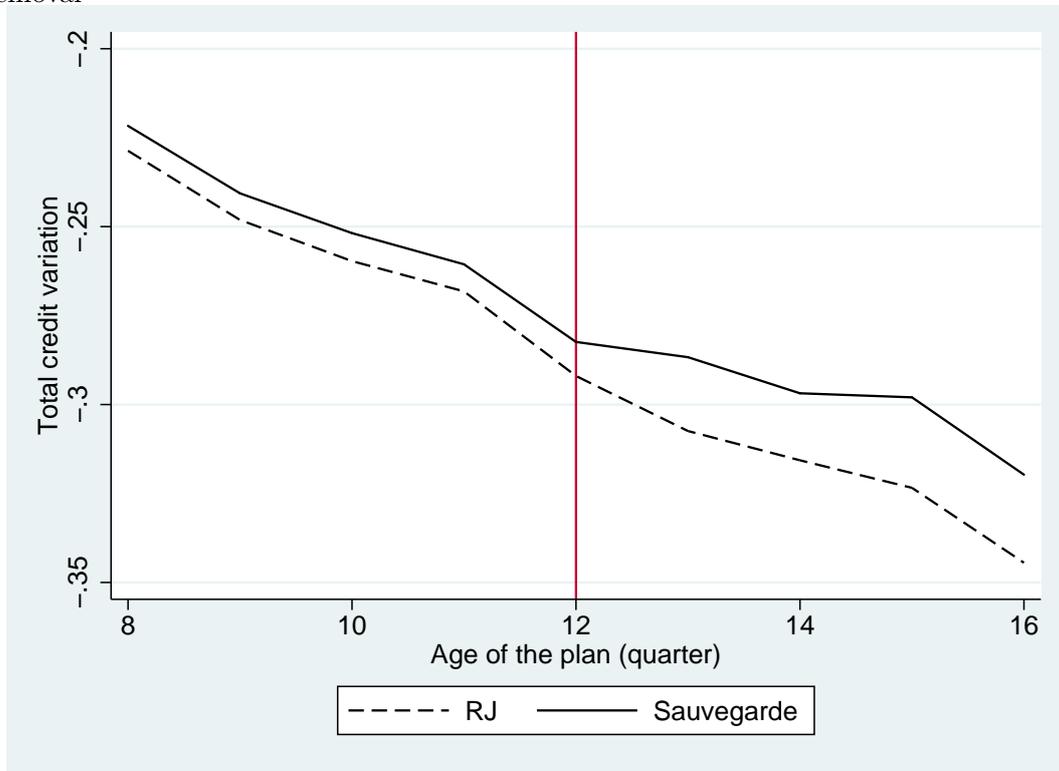
**Note:** Top image, represents the sharp drop in the proportion of Sauvegarde filers rated 5 around the flag removal at the 12th quarter of the plan. Bottom image, represents the sharp drop in the proportion of RJ filers rated 6 around the flag removal at the 20th quarter of the plan. We read that 75% of RJ filers were rated 6 before the 20th quarter of the plan; they are only 10% in the 21st quarter.

Figure 3: Transition matrices of the firm rating around Sauvegarde flag removal



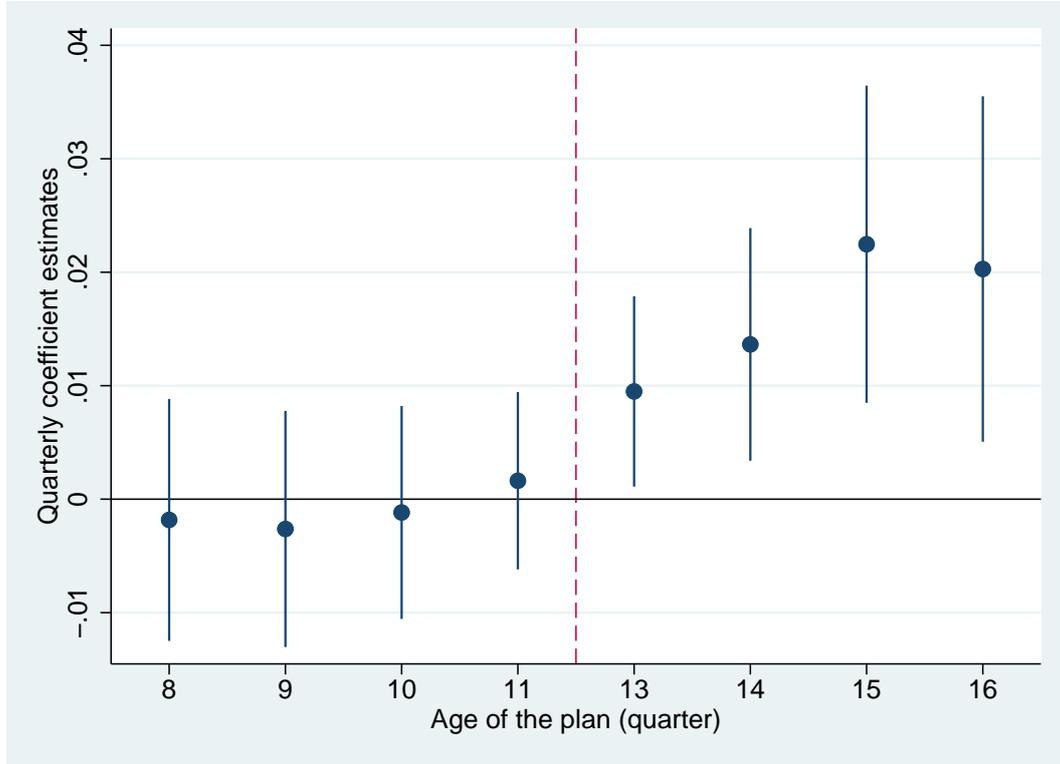
**Note :** Figure 3 shows the proportion of rated firms in Sauvegarde at each quarter of the plan around the flag removal. We read that 81% of Sauvegarde filers are rated 5 at the 11th quarter of their plan. This proportion drops to 35% after the flag removal in the 12th quarter.

Figure 4: Average credit growth for Sauvegarde and RJ filers around Sauvegarde flag removal



**Note :** Figure 4 shows the raw quarterly average credit variation for firm around the flag removal for treated firms (Sauvegarde filers, solid line) and controls firms (RJ filers, dashed line). The variation of credit is  $\Delta Credit_{i,t}$ , the quarterly variation of total credit compared to the firm's average level of credit the year before it filed for bankruptcy.

Figure 5: Quarterly effect of Sauvegarde flag removal on firm's credit



**Note :** Figure 5 reports difference-in-difference estimates  $\beta_q$  of the effect of the flag removal in Sauvegarde on the variation of firm's credit (see equation 3). The dependent variable is  $\Delta Credit_{i,t}$ , the quarterly variation of total credit compared to the firm's average level of credit the year before it filed for bankruptcy. Firms are tracked from four quarters before the flag removal to four quarters after it. The vertical red line identifies the Sauvegarde flag removal at  $q = 12$ . Standard errors are clustered at the firm level.

Figure 6: Relationship bank credit

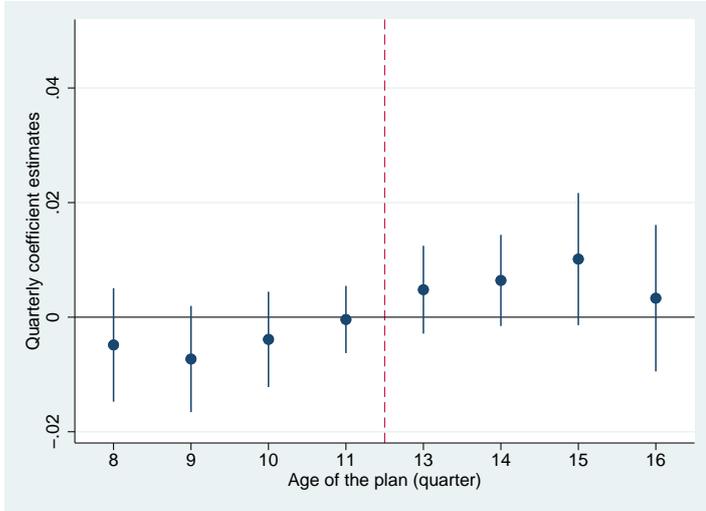
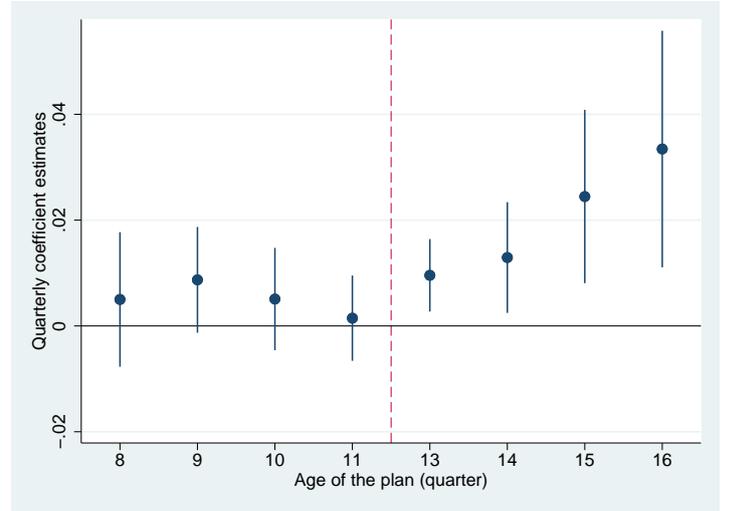


Figure 7: New bank credit



**Note :** Figures 7 and 6 reports difference-in-difference estimates  $\beta_q$  of the effect of the flag removal in Sauvegarde on the variation of firm's credit (see equation 3).  $\Delta Credit_{i,t}$  is split between new bank credit and relationship bank credit (see equations 7 and 8). Standard errors are clustered at the firm level.

Table 1: Banque de France's credit rating

Banque de France's credit rating	The firm's repayment capacity is:
3++	Excellent
3+	Very Strong
3	Strong
4+	Quite Strong
4	Good
5+	Quite Weak
5	Weak
6	Very Weak
7	Need specific attention
8	Threatened
9	Compromised
P	Bankruptcy procedure
0	No notation (no negative information)

**Note:** Table 1 reports a brief overview the Banque de France credit rating scale for firms.

Table 2: Summary Statistics

	Panel A: Firm-quarter characteristics					
	N	Mean	Median	St.Dev.	5th Pct.	95th Pct.
<i>Treated group: Sauvegarde firms</i>						
Bank Credit (K€)	8,322	387	163	660	33	1560
Long term/Total credit	8,281	0.460	0.435	0.420	0.000	1.000
Number of banks	8,322	1.782	1.000	1.273	1.000	4.000
Default	8,322	0.038	0.000	0.191	0.000	0.000
<i>Control group: RJ firms</i>						
Bank Credit (K€)	40,196	206	90	742	28	670
Long term/Total credit	39,891	0.428	0.310	0.426	0.000	1.000
Number of banks	40,196	1.405	1.000	0.892	1.000	3.000
Default	40,196	0.048	0.000	0.215	0.000	0.000
	Panel B: Firm-year characteristics					
	N	Mean	Median	St.Dev.	5th Pct.	95th Pct.
<i>Treated group: Sauvegarde firms</i>						
Turnover (K€)	4,814	1286.523	676.475	1784.494	76.570	5259.590
Asset (K€)	4,814	1059.814	543.089	1326.905	91.649	4165.202
Leverage (Total Debt/Total Asset)	4,801	1.147	0.923	0.925	0.444	2.393
Supplier Debt/Total Debt	4,796	0.183	0.135	0.156	0.017	0.503
Cash/Total Asset	4,801	0.114	0.072	0.123	0.002	0.378
Interest Coverage Ratio	3,559	222.603	57.580	499.373	-6.528	1012.325
Apparent Cost of Debt	4,316	0.286	0.018	1.390	0.000	0.967
Investment	4,668	0.034	0.008	0.066	0.000	0.166
#Employees	4,813	7.607	4.000	10.654	0.000	29.000
<i>Control group: RJ firms</i>						
Turnover (K€)	21,045	810.091	394.110	1266.385	57.360	3003.250
Asset (K€)	21,045	578.250	297.124	893.206	30.688	2046.000
Leverage (Total Debt/Total Asset)	20,544	1.416	1.087	1.128	0.502	3.413
Supplier Debt/Total Debt	20,446	0.185	0.142	0.153	0.022	0.502
Cash/Total Asset	20,544	0.101	0.059	0.116	0.001	0.353
Interest Coverage Ratio	12,823	211.961	62.752	457.715	-2.320	945.701
Apparent Cost of Debt	16,573	0.373	0.014	1.622	0.000	1.566
Investment	19,550	0.034	0.008	0.065	0.000	0.168
#Employees	21,036	5.778	3.000	8.497	0.000	23.000

Table 2: Summary Statistics – continued

	Panel C: Firm characteristics					
	N	Mean	Median	St.Dev.	5th Pct.	95th Pct.
<i>Treated group: Sauvegarde firms</i>						
Length of the plan (years)	825	9.566	10.000	1.212	7.000	10.000
<i>Control group: RJ firms</i>						
Length of the plan (years)	3,475	9.590	10.000	0.995	8.000	10.000
	Panel D: Firm-bank characteristics					
	N	Mean	Median	St.Dev.	5th Pct.	95th Pct.
<i>Treated group: Sauvegarde firms</i>						
Age of the relationship (years)	3,131	4.650	4.500	3.358	0.250	10.500
Relationship during bankruptcy	3,131	0.755	1.000	0.430	0.000	1.000
Main relationship	3,131	0.470	0.000	0.498	0.000	1.000
Same French departement	3,092	0.459	0.339	0.467	0.000	1.000
<i>Control group: RJ firms</i>						
Age of the relationship (years)	12,962	4.480	4.500	3.215	0.250	10.000
Relationship during bankruptcy	12,962	0.744	1.000	0.436	0.000	1.000
Main relationship	12,962	0.609	1.000	0.486	0.000	1.000
Same French departement	12,635	0.439	0.198	0.465	0.000	1.000

**Note:** Table 2 reports sample summary statistics for key variables. The sample period is from 2012 to 2019. To control for sample attrition, we restrict our sample to firms which plan was adopted between 2008 and 2016 and which was carried on for at least 4 years. We remove holdings, agricultural firms and subsidiary firms. We follow firms from four quarters before the flag removal to four quarters after it. Each panel compares the treatment group, Sauvegarde filers, to the control group, RJ filers. Panel A reports firm's quarterly credit information obtained from the French credit register. Panel B reports firms' annual financial variables obtained via FIBEN. Panel C reports information of firms' restructuring plan obtained from the BODACC. Panel D reports information of the firm-bank relationships characteristics obtained from the French credit register. Interest Coverage Ratio = EBITDA / Interest Expenses. Apparent Cost of Debt = Interest Expenses / Debt. Investment = (Tangible + Intangible + Financial Investments) / Lagged Total Assets. The dummy "relationship during bankruptcy" equals one if the firm-bank relationship was active when the firm filed for bankruptcy. The dummy "main relationship" equals one if the firm-bank relationship represents the firm's largest share of bank credit. The dummy "same French department" equals one if the firm's headquarters and the bank's local branch are in the same French department.

Table 3: Effect of flag removal on firm's credit

	$\Delta$ Credit		alt. $\Delta$ Credit
	(1)	(2)	(3)
Post	-0.00591*** (0.001)		0.00253 (0.252)
Treated $\times$ Post	0.0169*** (0.005)		0.00715** (0.016)
q=8 $\times$ Treated		-0.00183 (0.737)	
q=9 $\times$ Treated		-0.00263 (0.621)	
q=10 $\times$ Treated		-0.00117 (0.806)	
q=11 $\times$ Treated		0.00162 (0.684)	
q=13 $\times$ Treated		0.00949** (0.026)	
q=14 $\times$ Treated		0.0136*** (0.009)	
q=15 $\times$ Treated		0.0225*** (0.002)	
q=16 $\times$ Treated		0.0203*** (0.009)	
Firm FE	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓
Observations	48,518	48,518	48,147
Adj. R <sup>2</sup>	0.926	0.926	0.029
Adj. Within R <sup>2</sup>	0.001	0.005	0.000

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** Table 3 reports difference-in-difference estimates of the effect of the flag removal in Sauvegarde on the variation of firm's credit. The dependent variable columns (1) and (2) is the quarterly variation of total credit compared to the firm's average level of credit the year before it filed for bankruptcy. The dependent variable column (3) is the quarterly credit change. Column (1) and (3) reports the results of equation 2 and column (2) of equation 3. *Treated* takes the value of 1 for Sauvegarde filers, and *Post* takes the value of 1 when the debt-restructuring plan is older than 12 quarters. Firms are tracked from four quarters before the flag removal to four quarters after it. Standard errors are clustered at the firm level.

Table 4: Effect of flag removal on firm's new banking relationship

	Pr(New Bank)			
	(1)	(2)	(3)	(4)
	Logit	Logit	OLS	OLS
Post	-0.179*** (0.004)	0.0501 (0.426)	-0.00273 (0.200)	0.00535 (0.231)
Treated $\times$ Post	0.605*** (0.000)	0.343*** (0.003)	0.0186** (0.038)	0.0225** (0.046)
Lag Log(Total assets)		0.415*** (0.000)		0.0202*** (0.000)
Length of the plan (years)		-0.0295 (0.244)		-0.00296 (0.290)
Long term/Total credit		-0.612*** (0.000)		-0.0253*** (0.000)
Leverage		-0.0799** (0.034)		-0.00115 (0.612)
Firm FE	✓		✓	
Quarter FE	✓			
Quarter $\times$ Industry FE		✓	✓	✓
Observations	6,299	27,272	48,518	28,369
Adj. R <sup>2</sup>			0.425	0.058
Adj. Within R <sup>2</sup>			0.000	0.015
Pseudo R <sup>2</sup>	0.004	0.106		

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** Table 4 reports difference-in-difference estimates of the effect of the flag removal on the probability of forming new bank lending relationship (see equation 6). The dependent variable  $NewBank_{i,q}$  equals 1 before  $q = 12$  if the firm starts borrowing from a new bank before  $q = 12$ , 0 otherwise; and equals 1 after  $q = 12$  if the firm starts borrowing from a new bank after  $q = 12$ , 0 otherwise. Columns (1) and (2) reports the results of a fixed-effects logit model, and columns (3) and (4) of a linear probability model. *Treated* takes the value of 1 for Sauvegarde filers, and *Post* takes the value of 1 when the debt-restructuring plan is older than 12 quarters. Firms are tracked from four quarters before the flag removal to four quarters after it. Standard errors are clustered at the firm level.

Table 5: Effect of the flag removal on less informed lenders

	$\Delta$ Credit		
	(1) Post-Bankruptcy Relationship	(2) Secondary Lender	(3) Distance
Post	-0.00846*** (0.000)	-0.0124*** (0.000)	-0.0157*** (0.000)
Treated $\times$ Post	0.0125*** (0.000)	0.0110** (0.034)	0.0161*** (0.000)
$D_{i,b,t}$	-0.0833*** (0.000)	-0.284*** (0.000)	-0.00858 (0.603)
$D_{i,b,t} \times$ Treated	-0.0245 (0.503)	-0.0198 (0.262)	-0.0136 (0.597)
$D_{i,b,t} \times$ Post	0.0438*** (0.000)	0.0349*** (0.000)	0.0342*** (0.000)
$D_{i,b,t} \times$ Treated $\times$ Post	0.00621 (0.827)	-0.00374 (0.650)	-0.0104 (0.399)
Firm FE	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓
Bank FE	✓	✓	✓
Observations	81,646	81,646	79,767
Adj. R <sup>2</sup>	0.833	0.879	0.833
Adj. Within R <sup>2</sup>	0.007	0.281	0.002

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** Table 5 reports difference-in-difference estimates of the flag removal depending on the depth of the bank-firm relationship. In all regressions, the dummy  $D_{i,b,t}$  equals one if the firm-bank relationship is not the most informationally powerful. In column (1),  $D_{i,b,t}$  equals 1 if the firm-bank relationship was not active when the firm filed for bankruptcy. In column (2),  $D_{i,b,t}$  equals 1 if the firm-bank relationship is not the firm's main relationship. In column (3),  $D_{i,b,t}$  equals 1 if the bank's local branch and the firm's headquarters are not located in the same French department. Standard errors are clustered at the firm level.

Table 6: Banks' solvency channel

	$\Delta$ Credit			
	(1)	(2)	(3)	(4)
Post	-0.00635*** (0.008)	-0.00529* (0.078)	-0.00480** (0.028)	-0.00419* (0.059)
Treated $\times$ Post	0.0184*** (0.004)	0.0160** (0.027)	0.0127*** (0.001)	0.0150*** (0.000)
Low Tier1	-0.00754* (0.094)	-0.00229 (0.636)	-0.00437 (0.580)	-0.00308 (0.794)
Treated $\times$ Low Tier1		-0.0207 (0.146)		0.0224 (0.431)
Post $\times$ Low Tier1		-0.00326 (0.495)		-0.0106 (0.145)
Treated $\times$ Post $\times$ Low Tier1		0.00798 (0.470)		-0.0298 (0.141)
Firm FE	✓	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓	✓
Bank FE			✓	✓
Observations	36,177	36,177	46,871	46,871
Adj. R <sup>2</sup>	0.920	0.920	0.869	0.869
Adj. Within R <sup>2</sup>	0.001	0.001	0.000	0.001

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note :** Table 6 reports difference-in-difference estimates of the flag removal depending on the level of solvency constraints faced by the banks. Estimates columns (1) and (2) are at the firm level where  $Low_{i,t-1}$  equals 1 if the lagged weighted average of the firm's banks' Tier 1 ratios is in the lower quartile of the distribution. Estimates columns (3) and (4) are at the firm-bank level and include bank fixed effects, and  $Low_{i,b,t-1}$  equals 1 if the banks' Tier 1 ratios are in the lower quartile of the distribution. Standard errors are clustered at the firm level.

Table 7: Effect of flag removal on firms' outcomes

	Financial outcomes			
	(1) Apparent Cost of Debt	(2) Interest Coverage Ratio	(3) Leverage	(4) Supplier Debt/ Total Debt
Post	-0.0675** (0.048)	6.867 (0.635)	0.000651 (0.965)	0.00225 (0.398)
Treated $\times$ Post	-0.0197 (0.496)	12.44 (0.392)	0.00941 (0.574)	-0.00756*** (0.008)
Firm FE	✓	✓	✓	✓
Year $\times$ Industry FE	✓	✓	✓	✓
Observations	6,850	5,145	8,847	8,827
Adj. R <sup>2</sup>	0.698	0.651	0.901	0.887
Adj. Within R <sup>2</sup>	0.001	-0.000	-0.000	0.001

	Economic real outcomes		
	(1) Investment	(2) $\Delta$ Turnover	(3) $\Delta$ Employment
Post	0.0000925 (0.970)	-0.00606 (0.558)	-0.0122 (0.438)
Treated $\times$ Post	0.00469** (0.049)	0.00946 (0.379)	0.00479 (0.760)
Firm FE	✓	✓	✓
Year $\times$ Industry FE	✓	✓	✓
Observations	8,460	7,120	7,141
Adj. R <sup>2</sup>	0.437	0.870	0.789
Adj. Within R <sup>2</sup>	0.000	-0.000	-0.000

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** Table 7 reports difference-in-difference results of the flag removal on firms' annual real outcomes. The top panel presents results on financial variables; Apparent Cost of Debt = Interest Expenses / Financial Debt. Interest Coverage Ratio = EBITDA / Interest Expenses. Leverage = Total Debt / Total Assets. Bottom panel presents results on economic variables; Investment = (Tangible + Intangible + Financial Investments) / Lagged Total Assets.  $\Delta$  Turnover and  $\Delta$  Employment are changes relative to the pre-bankruptcy period. All variables are winsorized at the 2% percentiles at both tails. Standard errors are clustered at the firm level.

Table 8: Effect of the flag removal on payment incidents

	Incident
	(1)
Post	-0.00142 (0.665)
Treated $\times$ Post	-0.00740 (0.163)
Firm FE	✓
Quarter $\times$ Industry FE	✓
Observations	49,447
Adj. R <sup>2</sup>	0.477
Adj. Within R <sup>2</sup>	0.000

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note:** Table 8 reports difference-in-difference results of the flag removal on the quarterly probability that firms experience a payment default, defined by receiving a credit rating of 7 or riskier. Standard errors are clustered at the firm level.

## Appendix A Propensity Score Matching

In my main specification, I compare firms in Sauvegarde and RJ under the assumption that the trend of my outcome variables would have evolved in the same way in the absence of treatment. This hypothesis of parallel trends does not require the outcome to be identical across the treated and control group, as the estimation differences out any time-invariant disparities. Nevertheless, in the following analysis I propose a robustness test that considers treated and control firms' heterogeneity in observable characteristics with a matching procedure.

As recommended by [King and Nielsen \(2019\)](#), I perform a nearest-neighbor matching method that minimizes the Mahalanobis distance between firms' characteristics. To do so, I select two matched control firms for each treated firm, with the possibility for control firms to serve as matches more than once to reduce the estimation bias (although it increases the variance).

Following the literature that uses matching methods in finance ([Almeida et al. \(2017\)](#), [Chernenko and Sunderam \(2012\)](#), [Lemmon and Roberts \(2010\)](#)), I match treated and control firms based on their financial characteristics the year before they filed for bankruptcy. The categorical variables include the year of adoption of the plan, the firm's industry, the region of its headquarters, and whether the firm had a significant (other than "0") rating prior to bankruptcy. The non-categorical variables include the length of the plan, the firm's size, investment, cash, leverage, and the share of long-term debt. All financial variables are winsorized at the 1% percentiles at both tails.

The first three columns of Table [A.1](#), top panel, present means, standard errors (in parentheses), differences of means, and t-statistics (in brackets) of the above-listed variables across the treatment and control groups before the matching procedure. On average and before matching, Sauvegarde filers are larger. They have more long-term credit at the onset of the bankruptcy procedure, more cash, and less leverage. I implement

the matching procedure with a logit regression at the firm level of the binary variable *Treated* on the firm characteristics. The regression is estimated on a cross-section of 626 Sauvegarde (treated) filers and 2,203 RJ (control) filers, for which I have enough financial information. The estimation results are presented in Table A.1, bottom panel, column (1) and reveal differences that are in line with those found in the comparison of Table A.1 Panel A.

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Insert Table A.1 here

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The three last columns of Table A.1, top panel, reveal the accuracy of the matching process with no statistically significant differences of means across any of the firm characteristics between the two groups. As a result of the matching process, I have 959 matched RJ filers to 701 Sauvegarde filers. Similarly, column (2) of Table A.1, bottom panel, reveals that none of the determinants are statistically significant in a logit regression restricted to the matched sample and accordingly weighted. We also note that the magnitudes of the coefficients estimates and the Pseudo-R<sup>2</sup> decline significantly from the Pre-Match to the Post-Match estimation, ensuring that the matching process has removed any meaningful differences along observable characteristics from the two groups of firms.

Table A.2 presents the results of the difference-in-difference estimations using the matched sample. Columns (1) and (2) present the result of the flag removal on the variation of credit, and column (3) on the probability of forming a new banking relationship. Results are statistically significant at the 5% level and in line with previous sections.

We notice that the matching estimator column (2) is 0.023, greater than the simple difference (0.017, Table 3).

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Insert Table A.2 here

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Table A.1: Propensity Score Matching

Table A.1 top panel presents means, standard errors (in parentheses), differences of means and t-statistics (in brackets) of observable characteristics across treated and control firms before and after the matching procedure. Treated firms are Sauvegarde filers, control firms are RJ filers. We implement a nearest-neighbor matching procedure with replacement, with a logit regression at the firm level of the variable *Treated* on the firm characteristics. Covariates include financial characteristics the year before firm filed for bankruptcy: the length of the plan, the firm's size measured as the log of its total assets, investment (tangible + intangible + financial investments over total assets), leverage (debt on total asset), the ratio of short term credit over total credit, cash over assets, whether the firm had a rating prior to bankruptcy, and its number of banks. Categorical variables include the year of adoption of the plan, the firm's industry and the region of its headquarters. Regression results are reported on Table A.1 bottom panel, column (1). Column (2) presents the results of the same logit regression estimated on the subsample of matched treatment and control observations, after matching.

	Pre-Match			Post-Match		
	Control	Treatment	Diff	Control	Treatment	Diff
	Summary Statistics					
Lenght of the plan (years)	9.601 (0.889)	9.526 (0.994)	0.075* [1.857]	9.564 (0.949)	9.534 (0.990)	0.031 [0.619]
Log(assets)	5.842 (1.023)	6.414 (1.117)	-0.572*** [-12.318]	6.137 (0.980)	6.404 (1.112)	-0.267 [-4.975]
Investment	0.051 (0.131)	0.046 (0.119)	0.005 [0.870]	0.042 (0.117)	0.046 (0.119)	-0.003 [-0.498]
Leverage	1.276 (0.644)	1.067 (0.484)	0.208*** [7.647]	1.133 (0.484)	1.069 (0.484)	0.063 [2.535]
Long term/Total credit	0.588 (0.364)	0.633 (0.364)	-0.044*** [-2.747]	0.617 (0.362)	0.633 (0.364)	-0.017 [-0.888]
Cash	0.065 (0.089)	0.068 (0.082)	-0.003 [-0.684]	0.063 (0.081)	0.068 (0.082)	-0.005 [-1.088]
Rating (Y/N)	0.501 (0.500)	0.586 (0.493)	-0.085*** [-3.820]	0.543 (0.498)	0.585 (0.493)	-0.042 [-1.626]
Log(Number of banks)	2.117 (1.766)	2.408 (2.182)	-0.291*** [-3.506]	2.233 (1.803)	2.410 (2.188)	-0.177 [-1.736]
Observations	2,326	641	-	900	641	-

Standards errors in parentheses, *t*-statistics in brackets

	Logit regression results	
	(1)	(2)
	Pre-Match	Post-Match
Lenght of the plan (years)	-0.0413 (0.427)	0.0537 (0.376)
Log(assets)	0.477*** (0.000)	-0.0527 (0.765)
Investment	0.0296 (0.941)	0.508 (0.283)
Cash	1.415** (0.011)	0.769 (0.347)
Leverage	-0.464*** (0.000)	0.0584 (0.725)
Long term/Total credit	0.505*** (0.003)	-0.126 (0.627)
Rating (Y/N)	0.182 (0.106)	0.00756 (0.959)
Log(Number of banks)	-0.0116 (0.911)	0.0448 (0.711)
Year of the plan	✓	✓
Industry	✓	✓
Region	✓	✓
Observations	2,971	1,540
Pseudo R <sup>2</sup>	0.115	0.078

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.2: Effect of flag removal on firm's credit on matched sample

	$\Delta$ Credit		Pr(New Bank)
	(1)	(2)	(3)
Post	-0.0147*** (0.004)		-0.0196*** (0.008)
Treated $\times$ Post	0.0263*** (0.003)		0.0331** (0.022)
q=8 $\times$ Treated		-0.00806 (0.324)	
q=9 $\times$ Treated		-0.00680 (0.388)	
q=10 $\times$ Treated		-0.00318 (0.660)	
q=11 $\times$ Treated		0.00360 (0.515)	
q=13 $\times$ Treated		0.0114* (0.057)	
q=14 $\times$ Treated		0.0170** (0.042)	
q=15 $\times$ Treated		0.0346*** (0.002)	
q=16 $\times$ Treated		0.0350*** (0.004)	
Firm FE	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓
Observations	12,193	12,193	12,193
Adj. R <sup>2</sup>	0.909	0.909	0.446
Adj. Within R <sup>2</sup>	0.004	0.009	0.002

*p*-values in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note :** Table A.2 reports difference-in-difference results of the flag removal on the matched sample. Treated firms are Sauvegarde filers; control firms are matched RJ filers. Dependent variable columns (1) and (2) is the quarterly variation of total credit, and column (3) is the probability of forming a new banking relationship. Standard errors are clustered at the firm level.

## Appendix B TWFE Robustness

As pointed out by [Roth et al. \(2022\)](#) and [De Chaisemartin and D’Haultfoeuille \(2022\)](#) in their review of the latest DID methodology literature, TWFE estimations are valid in specific conditions: when the parallel trends assumption is met, everyone is treated at the same time, and the effect is homogeneous between groups and over time. However, in case of treatment effects heterogeneity or invalid parallel trends, the TWFE method can suffer from severe pitfalls that may invalidate the results. This section addresses most of them with the statistical tests suggested by the most recent literature.

### B.1 Heterogeneous treatment effect

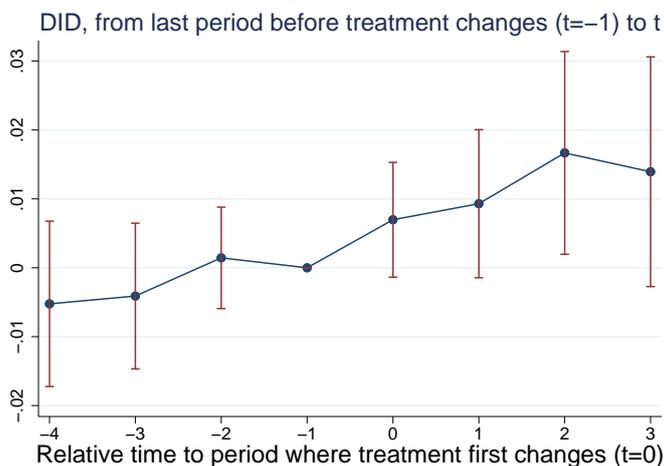
[De Chaisemartin and D’Haultfoeuille \(2020\)](#), [Borusyak and Jaravel \(2018\)](#) and [Goodman-Bacon \(2021\)](#) highlight that TWFE regressions may not always estimate a convex combination of treatment effects in the presence of negative weights. In the worst-case scenario, it could mean that the DID estimates a positive effect even though the treatment effect is strictly negative for every observation. The next section questions whether this could be the case in my framework.

On the one hand and following [De Chaisemartin and D’Haultfoeuille \(2020\)](#) analysis, the probability of having negative weights in my setup is small because (i) the treatment is binary, (ii) there are no always-treated and no time periods where most groups are treated, and (iii) the `twowayfeweight` package by [De Chaisemartin et al. \(2019\)](#) reveals the absence of negative weight in the sample.

On the other hand, I have so far assumed that the treatment effect is homogeneous across units (as an average of unit-level treatment effect). However, my framework has more than two time periods, and units have different treatment timings. Even if my weights are non-negative, they could be poorly estimated in case of time or group heterogeneity. I further test my estimates’ validity by implementing methods that are

robust to possible time or group heterogeneity. Following [De Chaisemartin et al. \(2019\)](#), I first implement the DID design `did_multiplegt` that is robust to dynamic treatment effects under the parallel trends assumption. This estimator is represented in [Figure A.1](#) and is a weighted average unbiased under heterogeneous and dynamic effects. The Figure shows that the coefficients pre-treatment are not statistically different from 0, *as per* parallel trends hypothesis. Following the treatment, the coefficients are positive and statistically different from zero at the 5% level at  $t + 3$ , and at the 10% level at  $t + 1$ ,  $t + 2$  and  $t + 4$ . The important takeaway is that the results are robust to introducing time and group heterogeneity.

Figure A.1: Time- and group-robust DID estimator



[Figure A.1](#) shows that the coefficients are robust to the introduction of time and group heterogeneity.

In the same vein and as pointed out by [Sun and Abraham \(2021\)](#), the DID coefficient estimate can be biased and the parallel trends assumption violated if the treatment effect is heterogeneous across cohorts. To rule out this potential pitfall, I follow [Sun and Abraham \(2021\)](#) and estimate the weight associated to the pre-trend coefficient using the package `eventstudyweights` ([Sun \(2020\)](#)). [Figure A.2](#) shows that the weights have a zero magnitude for lags of treatment. This would imply that the effects are homogeneous

across cohorts. This result follows the properties described in [Sun and Abraham \(2021\)](#) and is important as it alleviates the concern that the pre-trend coefficients may be contaminated by treatment effects cohort-heterogeneity and, therefore, invalid.

Figure A.2: Estimated weights underlying pre-trend coefficient

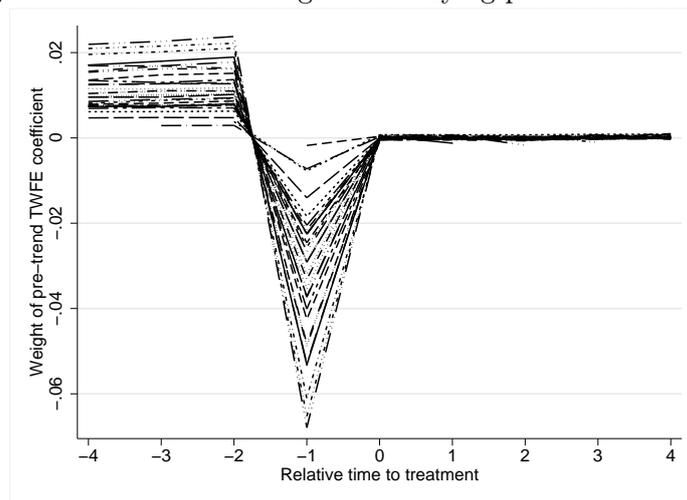


Figure A.2 shows the weights underlying the pre-trend coefficient two quarters from the flag removal. Each line is a different cohort from 2012 Q1 to 2019 Q4.

## B.2 Parallel trends hypothesis

So far, I have mainly tested the robustness of my results to time, group, or cohort heterogeneity under the parallel trends hypothesis. The next step is to challenge this last assumption.

Why would the control and treated groups have similar trends in my setup? One could argue that firms that file for the Sauvegarde procedure differ from those that file for the RJ procedure and that these differences may prevent the parallel trend assumption from holding. For instance, and as described in [Epaulard and Zapha \(2022\)](#), there may be a selection bias at the onset of the procedure. Managers that choose to file for Sauvegarde do so voluntarily as a preventive means to avoid insolvency, while the RJ procedure is

mandatory for already insolvent firms. Managers that chose Sauvegarde over RJ may present managerial skills or other unobservable characteristics that I need to account for, as they may lead to differences in outcome.

Although it is impossible to test the parallel trends *per se*, it is possible to mitigate the fear that a selection bias may invalidate them. I first note in Figure A.3 that the Sauvegarde and RJ repayment plans of a small sample of firms appear to be strictly identical. This descriptive evidence illustrates that the two groups of firms follow the same trajectory. Also, [Epaulard and Zapha \(2022\)](#) has proven several interesting points. First, the authors show that the selection bias at the onset of the procedure is not the main driver of the bankruptcy procedure outcome. Second and more importantly, they show that once a debt-restructuring plan has been adopted, the survival of the firms in RJ and Sauvegarde are identical. This previous research provides solid proof that the selection bias at the onset of the procedure does not impact the firm's outcomes once the firm has been restructured. This result is meaningful in my framework, where I study firms after the bankruptcy procedure.

Figure A.3: Plan repayment schedules at different horizons

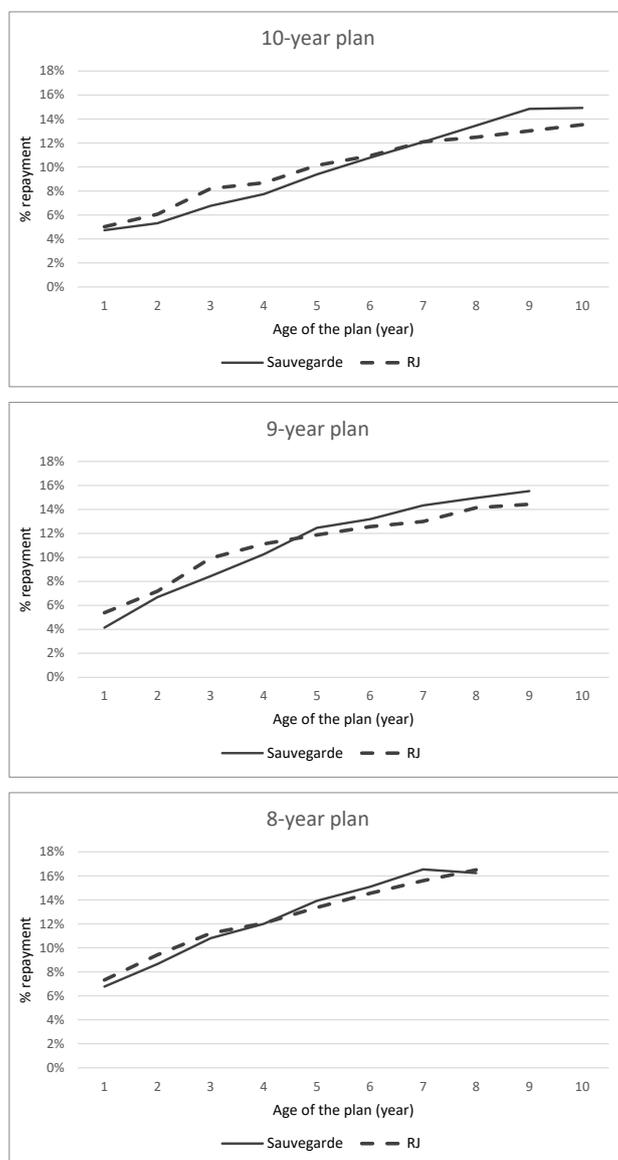


Figure A.3, from [Despierre et al. \(2018\)](#) analysis, shows repayment schedules of a small sample of firms that filed for Sauvegarde and RJ in the Commercial Court of Paris between 2006 and 2015. The sample contains 59 Sauvegarde filings and 78 RJ filings that obtained a debt-restructuring agreement with the detail of their yearly repayment prevision: 13 Sauvegarde filers and 27 RJ filers that obtained a debt-restructuring plan at the 10-year horizon, 11 Sauvegarde filers and 31 RJ filers at the 9-year horizon, and 13 Sauvegarde filers and 12 RJ filers at the 8-year horizon. At the 10-year horizon, I observe that firms start repaying an average of 5% per year from the first year until 15% in the tenth year. The same increasing pattern is followed for firms with a shorter plan. Most importantly, in this sample, Sauvegarde and RJ's repayment schedule is strictly identical.

I next turn to statistical tests described in the literature. In my model, I introduce firm fixed effects that control for any time-unvarying factors at the individual level. The last remaining concern is that there subsist time-varying characteristics that may have differentially affected the outcome of the treated group. I follow [Callaway and Sant'Anna \(2020\)](#) and their package `cscdid` to test for the plausibility of the parallel trend assumption. One important takeaway of this paper is that the parallel trend may hold conditioned on observed covariates. I perform their suggested test to ponder whether my parallel trend assumption is valid or better off conditioned on observed covariates.

Without covariates, the Cramér-von Mises test for the parallel trend rejects the parallel trend assumption at the 10% level (p-value = 0.0743). When I introduce calendar time  $\times$  industry fixed effects as covariates, the results illustrated in [Figure A.4](#) confirm the parallel trend hypothesis that the pre-trends coefficients are not statistically different from zero at the 10% level. [Figure A.4](#) further confirms the robustness of my result to dynamic treatment effects: the coefficients post-treatment are positive and significant at the 10% level at  $t + 3$ , as already suggested by the previous heterogeneity-robust tests. Conditioned on calendar time  $\times$  industry fixed effects, the Cramér-von Mises test indicates a p-value of 0.0929 for the parallel trends plausibility test. Thus, my setup seems better off with calendar time  $\times$  industry fixed effects as covariates, which are included in all specifications.

Figure A.4: Heterogeneity-robust DID estimates under conditional parallel trends

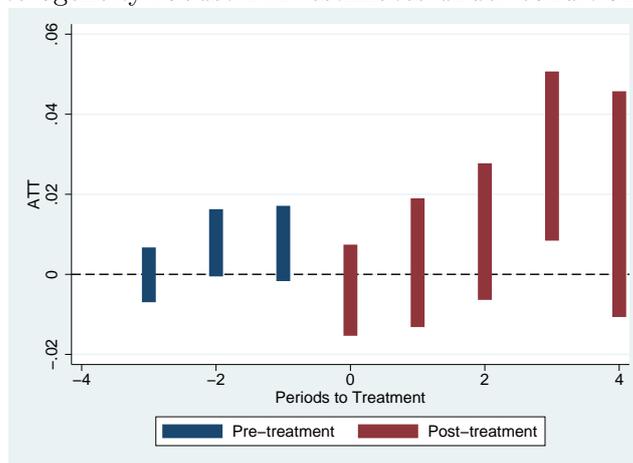
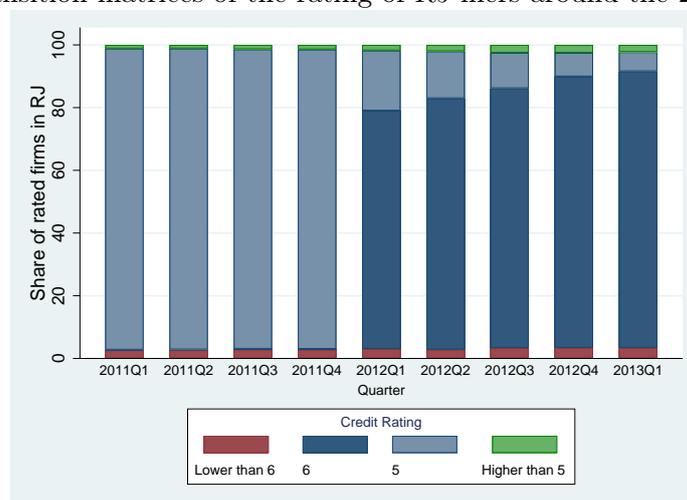


Figure A.4 confirms the robustness of the results to time and group heterogeneity under the parallel trend assumption conditioned on calendar time  $\times$  industry fixed effects.

## Appendix C The 2012 policy change

I exploit that, up to 2011, the credit rating of firms executing an RJ plan was 5. It was changed to 6 on January 1st, 2012, to convey better the credit risk carried by RJ filers. Figure A.1 presents the effect of this policy change on the rating of RJ filers between 2011 and 2013. At the end of 2011, 96% of RJ firms were rated 5. At the beginning of 2012, 83% were rated 6. RJ firms knew an exogenous rating change uncorrelated to their financial characteristics, but due to a change in the law.

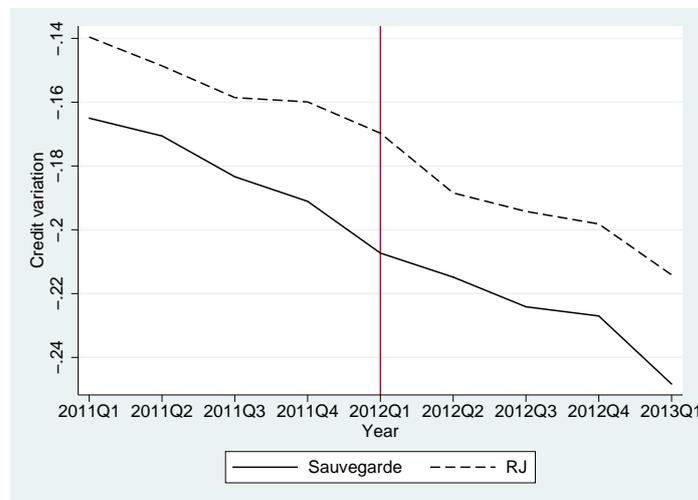
Figure A.1: Transition matrices of the rating of RJ filers around the 2012 policy change



**Note :** Figure A.1 describes the proportion of rated RJ filers in each quarter of the plan around the 2012 policy change. For example, we read that 96% of RJ filers were rated 5 in Q4 2011, and 86% were rated 6 in Q1 2012 after the policy change. The sample includes RJ filers whose plan was carried on for at least three years between 2011 and 2013.

Using a two-way fixed effects difference-in-difference design, I want to estimate the impact of the credit rating change on the firm credit variation. I compare RJ filers (treated group) with Sauvegarde filers (control group). As extensively explained in the paper, Sauvegarde firms form an ideal control group as they present the same plan characteristics as RJ filers, and their rating remained constant, set to 5 between 2011 and 2013. I focus on firms in the first three years of executing their plan and which plans lasted for at least

Figure A.2: Average credit growth for Sauvegarde and RJ filers around the 2012 policy change



**Note :** Figure A.2 shows the raw quarterly average credit variation for firm around the policy change for Sauvegarde filers (solid line) and RJ filers (dashed line). The variation of credit is  $\Delta Credit_{i,t}$ , the quarterly variation of total credit compared to the firm's average level of credit the year before it filed for bankruptcy. The sample includes RJ and Sauvegarde filers whose plan was carried on for at least three years, and I observed before the 3rd year of the plan, between 2011 and 2013.

three years. Figure A.2 shows the average credit growth of the two groups between 2011 and 2013. The parallel trends assumption requires that the credit growth follows the same trend before 2012, which we can argue is the case. Figure A.3 supports this assumption.

As previously explained, the policy change is intended to better signal the risk carried by firms undergoing restructuring after a RJ. We observe here the intensive margin: if banks already in a banking relationship with the firm are impacted by this exogenous rating change, we would expect  $\beta$  to be different from zero.

I run an alternative version of equation 2:

$$\Delta Credit_{i,t} = \beta (Post2012 \times Treated^i) + \gamma_q + \gamma_i + \gamma_{s \times t} \quad (9)$$

where  $Post2012$  is a dummy that equals 1 after 2012, and  $Treated^i$  equals 1 for RJ filers and 0 for Sauvegarde filers. I follow firms from four quarters before to four quarters

after the policy change. Unlike the main specification, the exogenous shock occurs at a specific date, regardless of the plan’s age. Therefore, I introduce  $\gamma_q$  for quarter-of-the-plan fixed effects. All the other variables are the same as described before, and the standard errors are clustered at the firm level.

Results are presented Table A.3. The coefficient  $\beta$  is not significantly different from 0, suggesting that the downgrade of credit rating did not cause a change in credit variation. Figure A.3 confirms this result. Although the first quarters after the change in rating are rather negative, they are not statistically different from zero.

Table A.3: Effect of 2012 change of rule on firm’s credit

	(1)
	$\Delta$ Credit
Treated' $\times$ Post2012	0.00406 (0.34)
Firm FE	Yes
Quarter $\times$ Industry FE	Yes
Quarter of the plan dummies	Yes
Observations	22,836
Adj. R <sup>2</sup>	0.918
Adj. Within R <sup>2</sup>	-0.000

*t* statistics in parentheses

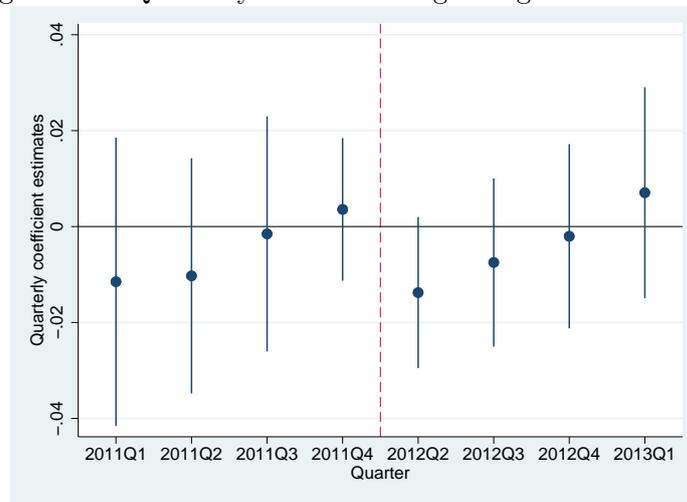
\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Note :** Table A.3 reports difference-in-difference estimates of the effect of the rating change in RJ on the variation of firm’s credit (see equation 9). The dependent variable is  $\Delta Credit_{i,t}$ , the quarterly variation of total credit compared to the firm’s average level of credit the year before it filed for bankruptcy. *Treated'* takes the value of 1 for RJ filers, and *Post2012* takes the value of 1 after 2012. The vertical red line identifies the policy change in 2012. Firms are tracked from four quarters before the policy change to four quarters after it. Standard errors are clustered at the firm level.

There are several reasons for this result. First, banks dealing with restructuring firms process information on past default internally. Typically, an internal credit rating is assigned to the firm. In the case of banks seeking to recover their restructured credit, this rating often remains unchanged until the restructured credit is fully repaid. This internal bank credit rating has probably not changed as of January 1, 2012. Therefore, it is logical that banks do not change their lending behavior. On the other hand, the rest of

the paper previously discussed the bank’s solvency as a transmission channel, and did not find that this channel came into play when the firm’s credit rating changed from 5 to 0. Assuming that the change in credit rating from 5 to 6 worsens the risk carried by banks (which is debatable), it is unlikely given the previous results, that the bank’s solvency in this case impacts the banks’ credit supply. Finally, it should be noted that ratings 5 and 6 are both risky ratings. The change in rating – although exogenous – remains small, which may explain the absence of a flagrant effect.

Figure A.3: Quarterly effect of rating change on firm’s credit



**Note :** Figure A.3 reports difference-in-difference estimates  $\beta_q$  of the effect of the policy change on the variation of firm’s credit (see equation 3). RJ filers are compared to Sauvegarde filers. The dependent variable is  $\Delta Credit_{f,t}$ , the quarterly variation of total credit compared to the firm’s average level of credit the year before it filed for bankruptcy. Firms are tracked from four quarters before the policy change to four quarters after it. Standard errors are clustered at the firm level.