How does the Ricochet Covid-19 Government-Backed Loan influence Belgian Small and Medium Enterprises?

Auteur : Rahmawati Safitri, Adelia
Promoteur(s) : Guillot, Malka
Faculté : HEC-Ecole de gestion de l'Université de Liège
Diplôme : Master en sciences de gestion, à finalité spécialisée en Financial Analysis and Audit
Année académique : 2023-2024
URI/URL : http://hdl.handle.net/2268.2/20939

HOW DOES THE RICOCHET COVID-19 GOVERNMENT-BACKED LOAN INFLUENCE BELGIAN SMALL AND MEDIUM ENTERPRISES?

Jury :
Supervisor :
Malka GUILLOT
Readers :
Wouter TORSIN
Sousso BIGNANDI

Master Thesis by
Adelia RAHMAWATI SAFITRI
For a degree in Master of Economic Sciences, specialised in Financial Analysis and Audit
Academic year 2023/2024

Acknowledgement

I would like to express my heartfelt gratitude to my master thesis supervisor, Malka Guillot for accepting my subject proposal. Her engaging Python course was a significant factor in my decision to pursue quantitative research and submit my proposal. I am deeply appreciative of her expert guidance and her willingness to assist me, even during evenings, to resolve modelling issues.

I also wish to acknowledge, with immense gratitude, the unwavering support, patience, and love of my family: my parents, Fitri and Frédéric; my sisters, Melyana and Chloé; my grandparents, Danielle and Jean-Pol. Their encouragement has been my driving force, and I hope I have made them proud.

Last but not least, a special thank you to Alex, whose boundless patience and continuous encouragement have been invaluable. He always encouraged me to give it my best. To my best friend and partner, I am deeply grateful.

Remerciements

Je tiens à exprimer ma profonde gratitude à la promotrice de mon mémoire de master, Malka Guillot, pour avoir accepté mon sujet. Son cours fascinant sur Python a grandement influencé ma décision de me lancer dans la recherche quantitative et de soumettre ma proposition de sujet. Je lui suis également reconnaissante pour son expertise et sa disponibilité, même le soir, pour m'aider à résoudre des problèmes de modélisation.

Je souhaite également remercier chaleureusement ma famille pour leur soutien indéfectible, leur patience et leur amour: mes parents, Fitri et Frédéric ; mes sœurs, Melyana et Chloé ; mes grands-parents, Danielle et Jean-Pol. Leur encouragement a été ma principale source de motivation, et j'espère les avoir rendus fiers.

Enfin, je voudrais exprimer ma profonde gratitude à Alex, dont la patience infinie et le précieux support ont été d'une valeur inestimable. Il m'a encouragée à donner le meilleur de moi-même. À mon meilleur ami et partenaire, je suis extrêmement reconnaissante.

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Acronyms

CNC Commision des Normes Comptables. 6

DiD Difference in Diffences. 2, 15, 18, 20, 21, 30, 39–41, LOT-1

EBIT Earnings Before Interest and Taxes. 25, 28

EC European Commission. 5, 6, LOT-1

EU European Union. 14

FPS Federal Public Service. 6, 7

HORECA hotels, restaurants and cafés. 8, 9, 12

IQR interquartile range. 31, 32

KDE Kernel Density Estimate. 31, 32

NACE nomenclature statistique des activités économiques. 12, 35, 37, ANN-1, LOF-1

NBB National Bank of Belgium. 8, 11

NBER National Bureau of Economic Research. 28

NRF non-reporting firms. 25

OECD Organisation for Economic Co-operation and Development. 10

ONSS Office National de la Sécurité Sociale. 7

SME Small and Medium-size Enterprise. 1–3, 5–14, 17, 18, 23, 25, 26, 28, 30, 35–39, 42–45, ANN-3, LOF-1

SOCAMUT Société des Cautions Mutuelles de Wallonie. 10–12

SOWALFIN Société Wallonne de Financement et de Garantie des Petites et Moyennes Entreprises. 11

Statbel Statistics Belgium. 7

VAT Value Added Tax. 7, LOF-1

1 Introduction

SMEs dominate the market by their sheer number and play a crucial role in driving economic growth and job creation (Rossi, 2017). In Belgium, SMEs are particularly significant, accounting for 99.9% of the total number of enterprises and employing approximately 1,148,985 individuals in the private sector alone (STATBEL, 2023; Economie, n.d.-a). Despite their economic importance, many SMEs face significant challenges in accessing finance (Franquesa and Vera, 2021). The Covid-19 pandemic, which began in 2019, has significantly disrupted economies worldwide, affecting businesses of all sizes (OECD, 2020). SMEs, in particular, have been severely impacted, exacerbating their long-standing financing problems. These businesses, typically less prepared for financial upheavals, have faced significant changes in supply chains, interruptions in business operations, liquidity shortages, and declining revenues. These challenges pose a threat to their survival (NBB, 2020).

In response to these challenges, governments and central banks worldwide have enacted extensive policy responses to alleviate the economic, financial, and social effects of the coronavirus. In Belgium, the Government has launched various policy initiatives at both federal and regional levels. These measures aim to provide financial support to financially sound companies through loans, capital investments, and guarantees (OECD, 2021a). One such measure, implemented in the Walloon region, is the "Ricochet-recovery" loan. This loan, distinguished by its 0% interest rate, differentiates it from other loans that SMEs may have obtained, making it an appealing option for businesses seeking financial support (OECD, 2022).

Factors such as the perceived risks associated with SMEs for banks and other investors can make it difficult for these businesses to access the finance they need. The said loan can help alleviate the perceived risks associated with SMEs, facilitating their access to finance. This can assist them in maintaining their operations and expanding their growth. By investigating this aspect, this study explores whether the loan has helped to mitigate the perceived risks associated with SMEs, thereby making it easier for them to secure finance.

To build on this, several studies have used credit spreads to gauge perceived risk and borrowing costs. For example, Caldara and Herbst, 2016 found that monetary policy shocks can significantly impact industrial output and corporate credit spreads. Akinci and Queralto, 2022 highlighted how macro-prudential policies can help mitigate financial crises by examining credit spread behaviour. Additionally, Gilchrist et al., 2014 discovered that credit spreads are crucial for investment decisions, as lower borrowing costs lead to better access to credit and increased investments. These studies highlight the importance of credit spreads in understanding financial dynamics and policy impacts.

One particularly relevant study by Kim, 2023 on government-backed financing in Korea after 2017 offers valuable insights on how policy impacts the credit spread. She finds that borrowing costs decreased more for firms eligible for government loans compared to those that were not, leading to increased investments and a lower exit rate for low-productivity firms. Inspired by Kim's findings, this study aims to explore whether the "Ricochet-recovery" loan can similarly improve credit availability and lower borrowing costs for Belgian SMEs. The mechanics of government-backed funding and its effect on credit spreads provide a useful comparative framework, despite the differences between the two countries.

The study draws on a extensive dataset of 9,263 SMEs from Bel-First, collected over the period spanning 2017 to 2022, resulting in a total of 55,578 firm-year observations. This dataset includes exhaustive details on each firm's financial obligations, workforce count, and aggregate asset value. Despite the constraint of not extending to data from 2023 onwards due to the unavailability of most firms' balance sheets, these comprehensive data points provide a solid foundation for scrutinising SMEs' financial standing and credit risk.

To investigate the impact of being eligible for the government-backed loan, an econometric statistical method known as the DiD approach is used. This method simplifies the comparison of changes in outcomes over time between a treatment group and a control group, defined based on the criteria for loan eligibility. By comparing these groups, the study aims to isolate the effect of the loan on various financial measures. This technique helps determine whether the observed changes are due to the loan itself or other external factors.

The first model uses a two-way fixed effects approach to determine whether the loan has impacted the credit spreads of SMEs after the policy was enacted. To ensure the validity of the results, the parallel trends assumption is essential. This assumption suggests that, without the treatment, the average trends for both the treatment group and the control group would be the same over time. Although this assumption cannot be directly verified, it can be supported by evidence of its plausibility through long-term effects. To further strengthen the results and eliminate false positives, a placebo test with two different fake-treatment periods is conducted (Huntington-Klein, 2022).

The results indicate that the loan policy has an effect on the credit spread of the treated group post-policy. Even when considering long-term effects and the placebo test, there is no evidence that the treatment effect pre-policy impacts the credit spread. Furthermore, the policy appears to decrease the credit spread. This finding suggests that the loan has a beneficial impact on the financial conditions of the eligible SMEs. The reduction in credit spread implies improved creditworthiness and lower borrowing costs for these firms.

Upon establishing the presence of a treatment effect, the study then examines the credit sensitivity to debt ratio, dividing the analysis in two sub-periods: before and after the treatment enactment. The findings reveal that eligible firms pre-policy have better external financial access compared to non-eligible firms, and this observation remains unchanged post-policy. Additionally, the sensitivity of credit spread pre-policy for non-eligible firms is insignificant, whereas it has a significant impact on eligible firms. This provides further evidence that the policy affects the intended firms during the pandemic.

These findings offer insightful information to policymakers by demonstrating how well the loan policy supported SMEs throughout the pandemic and emphasising the value of focused measures in reducing the negative consequences of economic downturns. These policies support the preservation of the general health of the economy by attending to the particular demands of SMEs. Policymakers can use these insights to design and implement similar policies in the future, ensuring SMEs receive the necessary support to navigate challenging economic conditions and maintain financial health. Encouraging a strong and resilient economic environment that can survive future shocks and uncertainties is a key function of well-designed financial interventions, as evidenced by the enhanced credit sensitivity and financial availability in eligible enterprises.

The structure of this master thesis is as follow. First, an overview of Belgian SMEs, detailing their characteristics and the economic environment in which they operate, is given, together with the introduction of the “Ricochet-recovery” loan, explaining its purpose and significance. Following this, a thorough literature review is presented, summarising existing research and identifying gaps that this thesis aims to address. The methodology section then outlines the models and statistical techniques used to analyse the data, providing a clear framework for the research. The results section presents the findings and interprets them, including the impact of the “Ricochet-recovery” loan on credit access and borrowing costs for eligible SMEs. Finally, the discussion addresses the limitations of the study and compares the findings to other relevant research, offering insights for future research.

2 Background

2.1 Background

This section aims at giving context to the problem addressed in the subsequent sections. By presenting a detailed examination of Belgian SMEs, and analysing the impact of the State-introduced "Ricochet-recovery" loan, the necessary background information will be provided for a reader to appreciate the significant impact of the pre-cited loan plan on SMEs economic performance. More specifically, the characteristics and key role of SMEs in the Belgian economy will be highlighted, together with the financing challenges they encounter. The "Ricochet-recovery" loan policy will then be introduced, with its key features and intended supporting role for financially healthy companies.

2.1.1 Belgian SMEs

Although universally acknowledged and recognised, the term SME lacks a universally agreed-upon definition. Several reasons can explain this lack, including, but not limited to, the fact that (i) interpretations of the term vary between countries, and (ii) the term can be approached from different perspectives, such as legal and practical applicability (Montanari and Kocollari, 2020).

This research primarily explores the economic effects of a particular loan policy implementation on Belgian SMEs. Introducing the legal Belgian definition of SMEs, a broader perspective on existing definitions will be provided, establishing a framework for the remainder of this work and giving readers a thorough understanding of the subject and the context withing which the findings of this work are situated.

The EC has set out a classification system for SMEs in recommendation 2003/361/EC. According to this recommendation, an enterprise is classified as an SME if it meets specific criteria related to employee count, annual turnover, and total annual balance sheet. The recommendation further categorises SMEs into different types based on these criteria, as shown in table 2.1 (Commission, 2023).

Category	**Employees**	**Turnover or Balance Sheet Total [M€]**
Micro	< 10	< 2
Small	< 50	< 10
Medium-sized	< 250	< 50 or ≤ 43

Table 2.1: Company size classification following the EC 2003/361/CE recommendation.

In Belgium, however, there is no single, universally agreed-upon definition for SMEs. The Federal Public Service (FPS) Economy primarily classifies an enterprise as an SME based on the number of employees criterion provided by the EC

> *"The small and medium-sized enterprise (SME) is a company subject to VAT with fewer than 250 employees that is registered with the Crossroads Bank for Enterprises (BCE)."*Economie, n.d.-b

On the other hand, the Commision des Normes Comptables (CNC) (CNC, n.d.-a), a Belgian entity offering guidance to the Government and Parliament, and developing accounting doctrine, established specific criteria for small companies in Belgium in 2022. The term "SME" is traditionally used to denote a small business, with the "M" typically referring to medium-sized businesses. However, from a legal standpoint, these entities do not exist in Belgian company law. In reality, companies are either classified as micro, small, or not small, as shown in table 2.2 per the CNC's definition CNC, n.d.-b.

Company Type	**Employees**	**Turnover [k€]**	**Total Balance Sheet [k€]**
Micro	< 10	< 700	< 350
Small	< 50	< 9000	< 4500

Table 2.2: Classification of small and micro companies.

The "Ricochet-recovery" loan, a Government-backed initiative, is the primary focus of this master's thesis. This loan is described in a similar way to the CNC's definition of an SME in terms of the number of employees, categorising it as a company with less than 50 employees on average (CNC, n.d.-b; SOWALFIN, 2022). However, the financial requirements differ from those set by the CNC. Instead, it aligns more closely with the EC's definition of a "small" SME, which includes businesses with a maximum annual turnover or total balance sheet of less than EUR 10 million (Commission, 2023; SOWALFIN, 2022).

While the EC and CNC offer different definitions, the one chosen for this research is representative of the majority of SMEs in Belgium, accounting for approximately 99% of the market (STATBEL, 2023). Therefore, within the context of this thesis, an SME is defined as follows:

> *A company that employs 50 or fewer average employees and has a turnover or balance sheet of less than EUR 10 million. SOWALFIN, 2022*

This definition strengthens the validity and relevance of the research findings by representing the Belgian SME landscape (STATBEL, 2023) and adhering to the particular criteria of the Ricochet-recovery loan criterion (SOWALFIN, 2022).

SMEs Description and Their Importance in the Belgian Economy

The emphasis on SMEs in research is attributed to their pivotal role in the economy. SMEs, which account for 99% of businesses in Belgium, form the backbone of the Belgian economic landscape. As of the end of 2022, Belgium had 1,135,771 SMEs out of a total of 1,143,403 VAT-registered enterprises (STATBEL, 2023). To better understand their growth over recent years, figure 2.1 [1] illustrates a consistently positive growth trajectory from 2017 to 2022, with annual growth rates exceeding 3%. Although growth slowed from 4% in 2017 to 3.5% in 2019, it rebounded to over 4.4% in 2022. This upward trend highlights the resilience and significance

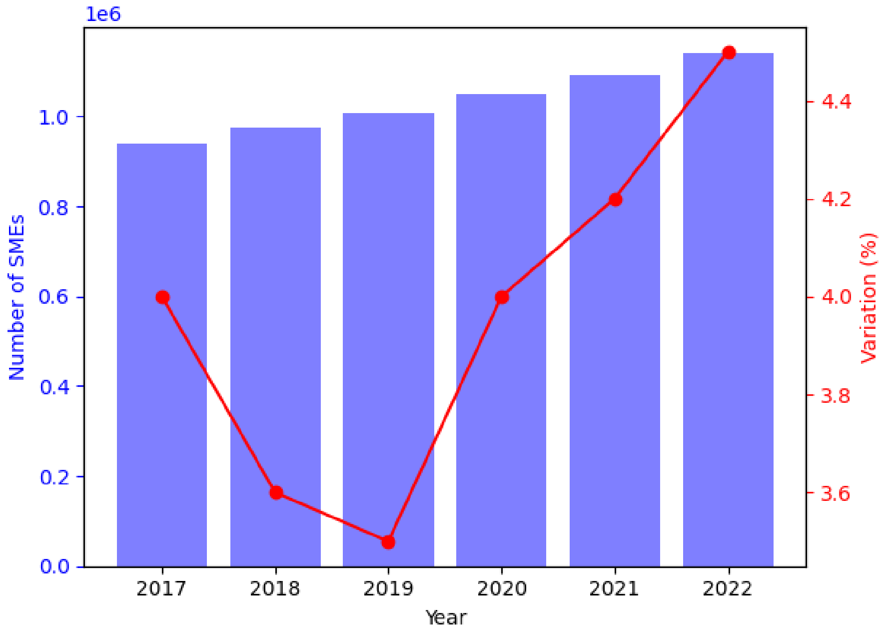

Figure 2.1: Number of VAT-registered SME and variation of SME from 2017 to 2022 in Belgium.

of SMEs as key drivers of economic progress. Understanding these trends from the perspective of authorities is crucial for developing policies that support and sustain SME growth.

The contribution of SMEs to employment is substantial. By 2022, SMEs accounted for 1,148,985 of the 3,084,684 occupied job positions in the private sector, representing 37.25% of all occupied posts. This underscores the significant role SMEs play in job creation. Additionally, SMEs constituted the majority of Office National de la Sécurité Sociale (ONSS) employer companies, accounting for 64.06%. The increase in the number of occupied posts from 2018 to 2022, with the exception of 2020, further highlights the importance of SMEs in maintaining employment levels and contributing to economic stability (Economie, n.d.-a).

The sectoral distribution of SMEs in Belgium reveals their diverse contributions to the economy. According to Statistics Belgium (Statbel), the top seven sectors play a crucial role in the SME landscape. These sectors include Professional, Scientific, and Technical Activities (223,491 enterprises), Wholesale and Retail Trade; Repair of Motor Vehicles (187,649 enterprises), Construction (156,859 enterprises), Other Service Activities (74,944 enterprises), Administrative and Support Service Activities (70,277 enterprises), Accommodation and Food Service Activities (63,817 enterprises), and Information and Communication (60,807 enterprises). Collectively, these sectors account for 837,844 enterprises, making up about 73.77% of all SME activities in Belgium, as shown in Figure 2.2 [2] . The remaining 297,927 enterprises are spread across various other economic activities (Economie, 2023).

While SMEs play a crucial role in the Belgian economy, they often lag in pursuing advanced technology and innovation compared to larger firms (OECD, 2021b). Recognising their importance, the Belgian government has implemented various initiatives to support these firms in their innovation efforts. These include grants, tax incentives, and support programs aimed at enhancing the research and development capabilities of SMEs (FPS, n.d.-a, n.d.-b). By investing

[1]This figure is derived from FPS Economie, n.d.-b, with the exclusion of SMEs employing between 50 and 249 workers, which are included in the original source.

[2]This figure is derived from FPS Economie, n.d.-a, with the exclusion of SMEs employing between 50 and 249 workers, which are included in the original source.

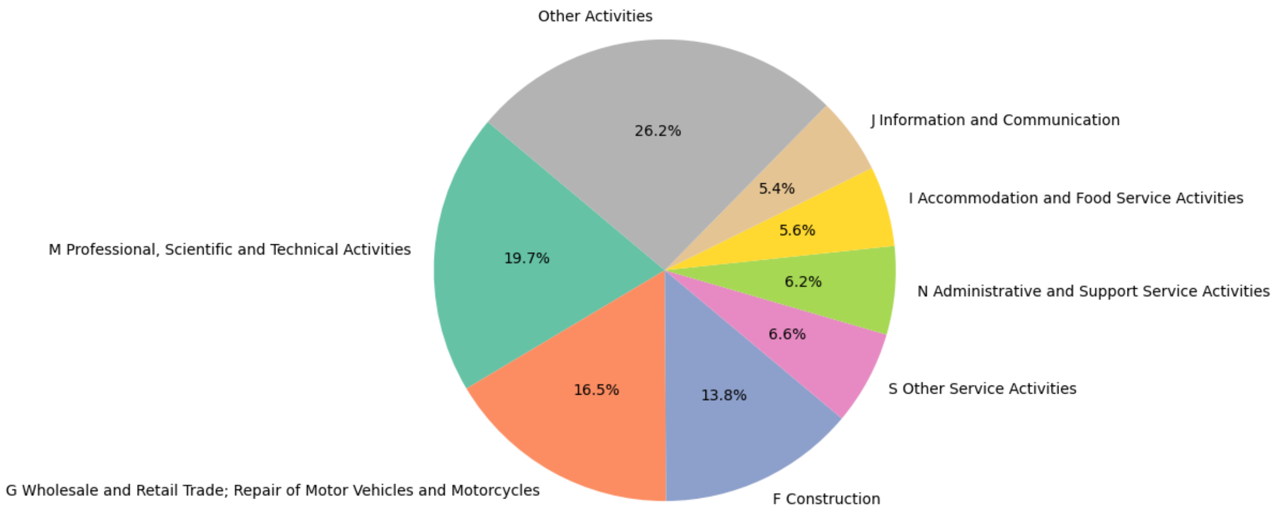

Figure 2.2: Belgian SMEs sectoral distribution.

in and fostering these entities, Belgium ensures that its SMEs remain competitive on a global scale, thereby driving economic growth and sustainability (Economy, n.d.).

The study and understanding of SMEs are of paramount importance due to their significant role in driving economic growth, job creation (Economie, n.d.-a), and ensuring the resilience of the Belgian economy (OECD, 2019). SMEs represent the majority of all businesses (STATBEL, 2023), generate a substantial portion of employment (Economie, n.d.-a), and contribute significantly to national prosperity (OECD, 2019). Insights into the dynamics of Belgian SMEs are essential for providing valuable perspectives on the overall health and future direction of the Belgian economy.

Impact of Covid-19 on SMEs

The Covid-19 pandemic has introduced unprecedented challenges for businesses (Belitski et al., 2022). Lockdown measures have significantly altered consumer behaviour, impacting both the production and demand for goods and services (nationale de Belgique, 2021). This in turn has not only affected incomes but also the labour market (Kalemli-Özcan, 2021). The uncertainty surrounding the recovery of these businesses has therefore become a major concern for the Government. Small businesses and specific sectors, such as hotels, restaurants and cafés (HORECA), were particularly vulnerable and severely affected by the Covid-19 crisis (Dhyne and Duprez, 2021).

Numerous studies have corroborated this observation. Notably, an analysis conducted by the National Bank of Belgium (NBB) revealed that the the economic repercussions were most severe during the first wave of infections. This period saw the most stringent lockdown measures, leading to significant disruptions in business operations. By the first quarter of 2021, the situation had become varied. Over a quarter of firms were still struggling to recover from the initial shock, while others had begun to recover. The HORECA sector, along with arts and entertainment, and personal services, recorded the weakest performance due to stringent restrictions on activity (Dhyne and Duprez, 2021).

The manufacturing and construction industries, which are amongst the top sectors where SMEs are concentrated (Economie, 2023), as shown in figure 2.2, also faced disruptions. Although these industries were not directly targeted by lockdown measures, their activities were significantly impacted due to supply chain interruptions and reduced demand (Dhyne and Duprez, 2021). The Belgian economy experienced a notable decline in industrial production, with many businesses temporarily scaling down or suspending operations (FPS, 2021).

These instances illustrate how performance has been impacted by supply and demand disruptions. As performance declined, SMEs experienced significant revenue losses due to the restrictions imposed to curb the virus's spread. According to Statista data, the tourist sector in Flanders and the Brussels-Capital Region had an expected revenue loss of 1.7 billion euros in 2020. This highlights the severe economic repercussions faced by the HORECA sector (Department, n.d.). Although the reopening of bars and restaurants in June 2020 had a positive impact on their revenue, the improvement was weak, and the sector continued to struggle (NBB, 2020).

The preceding section emphasised the pivotal role SMEs play in the Belgian workforce landscape, noting that approximately one-third of the private sector workforce is employed by these enterprises. However, during the pandemic, the number of posts filled by employees decreased by more than 2% from the previous year in 2020, as shown in figure 2.3 (Economie, n.d.-a), reducing the economic healthiness of SMEs and consequently impacting the entire Belgian economy. A study by the European Central Bank noted that without government support, the failure rate of SMEs would have increased significantly, leading to higher unemployment rates (Kalemli-Özcan, 2021).

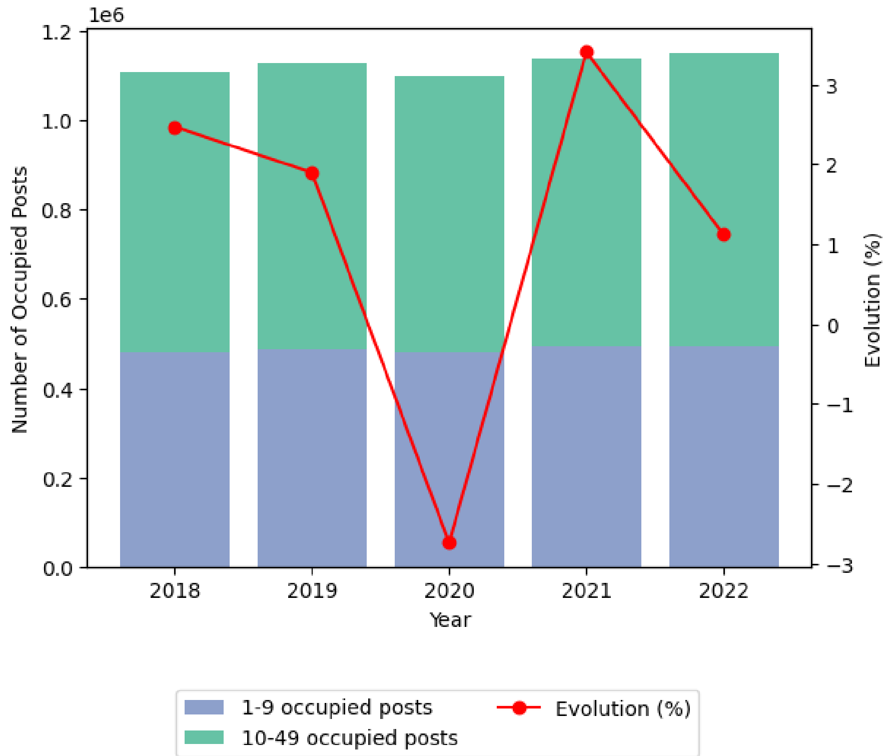

Figure 2.3: Occupied posts in Belgian SMEs and their evolution from 2018 to 2022.

The Belgian Government implemented various policy measures to support SMEs during this crisis, including financial aid, tax deferrals, and loan guarantees. These measures were essential in helping many SMEs stay afloat during the most challenging periods of the pandemic. The Belgian government's swift response to the crisis was crucial in preventing a more severe economic downturn. Financial aid packages were designed to cover operational costs, ensuring that businesses could continue to function despite reduced revenues. Tax deferrals provided temporary relief from financial obligations, allowing businesses to manage their cash flow more effectively. Loan guarantees facilitated access to credit, enabling SMEs to secure the necessary funds to maintain operations and invest in recovery efforts (OECD, 2022).

The Organisation for Economic Co-operation and Development (OECD) report on SME and Entrepreneurship Outlook 2021 highlighted the effectiveness of these measures in maintaining business continuity and preventing a wave of bankruptcies. Indeed, 41% of SMEs in Belgium have been able to access and combine government support, compared to 33.6% in the OECD. The Belgian government implemented a range of measures, including a EUR 100 million Flemish scheme to support companies affected by the pandemic. Additionally, a EUR 5 million scheme was introduced to support SMEs in the Brussels-Capital Region operating in the events and cultural sectors (OECD, 2021a).

These measures were crucial in helping businesses manage their cash flow and continue operations despite the economic challenges. Additionally, the government implemented temporary unemployment benefits to support firms affected by Covid-19. These benefits were increased from 65% to 70% to mitigate income loss for affected employees, allowing businesses to grant temporary unemployment to safeguard jobs (belgium.be, n.d.). The success of these policies has been recognised in various reports and studies, highlighting Belgium's proactive approach in stabilising the economy and ensuring the resilience of its SME sector (OECD, 2021a).

2.1.2 "Ricochet-recovery" Loan Policy

The Belgian government was instrumental in mitigating the economic fallout of the global pandemic caused by the Covid-19 pandemic. A series of financial support measures were introduced to assist SMEs. Among these initiatives, the "Ricochet-recovery" loan policy merits particular attention as a targeted effort to enhance the financial stability of SMEs (OECD, 2022). This policy was designed to provide subordinated loans in conjunction with bank moratoriums, offering additional financial support to businesses in need. By focusing on boosting cash flow and solvency, the Ricochet-recovery loan policy played a vital role in enabling SMEs to rebuild their working capital and invest in recovery efforts following the health crisis (SOWALFIN, 2022).

Key Characteristics

The "Ricochet-Recovery" loan was devised with the objective of providing assistance to businesses that have been adversely impacted by the global health crisis precipitated by the Covid-19 virus. The loan comprises two components: a bank loan and a subordinate loan from Société des Cautions Mutuelles de Wallonie (SOCAMUT). Both are designed to address businesses' treasury needs. The bank loan may be either new or existing, with a moratorium of at least six months, guaranteed by SOCAMUT to provide additional security for the bank. This ensures that businesses have the necessary funds to navigate the financial challenges they face. By providing this dual support, the loan aims to stabilise businesses during these uncertain times. The combination of these elements makes the "Ricochet-recovery" loan a comprehensive financial aid package.

Three options are available for consideration: a new bank loan guaranteed by SOCAMUT up to 75% with a complementary SOCAMUT loan, a moratorium of at least sixth months on an existing bank loan with a complementary SOCAMUT loan, or a combination of both. This flexibility permits businesses to select the optimal option for their financial circumstances, thereby ensuring comprehensive assistance. The capacity to adapt the loan to specific requirements is vital for businesses confronting diverse challenges. By offering these three possibilities, the "Ricochet-recovery" loan strives to provide comprehensive support to businesses in need. This adaptability is a pivotal feature of the product, ensuring its alignment with various financial requirements.

The total financing available under the “Ricochet” scheme is limited to EUR 100,000, although it can be augmented by combining it with other Société Wallonne de Financement et de Garantie des Petites et Moyennes Entreprises (SOWALFIN) group products for a comprehensive financial package. The SOCAMUT loan can be up to EUR 50,000, aligning with the new bank loan amount, deferred capital repayments, or both. The loan duration can be up to 10 years, including deferment, thereby providing a long-term solution. This extended duration allows businesses to financially recover and grow. The combination of these features makes the "Ricochet-recovery" loan a robust financial tool for businesses. By combining these elements, businesses can access a well-rounded financial support system.

The loan duration may be aligned with the terms of the new bank loan, the residual duration of the loan with a moratorium, or a combination thereof. he deferment period is a minimum of six months longer than that permitted by the bank, with a maximum of two years. The repayment schedule is on a quarterly basis, with a constant capital amount and an interest rate of 0%. No guarantee is required from the company or entrepreneur, which makes the loan accessible to businesses with limited collateral. This accessibility ensures that even businesses with limited resources can benefit from the financial support provided by the "Ricochet-recovery" Loan. By removing the need for collateral, the loan becomes a viable option for many struggling businesses.

Eligibility Criteria

The eligibility criteria for the "Ricochet-recovery" loan are rigorous and comprehensive. The loan is primarily targeted at SMEs. To qualify, these businesses must have their operational headquarters established in Wallonia. Furthermore, the investment financed through the intervention of SOCAMUT must be directed towards this operational headquarters. In addition to these geographical requirements, eligible businesses must also meet specific financial stability conditions. Lastly, they must operate within designated business sectors to qualify for the loan. These criteria ensure that the financial support is directed towards businesses that are both strategically important and financially viable.

Financial stability is a fundamental requirement for eligibility. A business is considered to be experiencing financial difficulty if, after operating for at least three years, its equity is reduced to less than half of the subscribed capital, with a minimum of a quarter of this capital having been lost over the last twelve months. Alternatively, financial difficulty can be determined by the presence of conditions that warrant submission to a collective insolvency procedure. This is particularly relevant when a business undergoes a judicial reorganisation procedure, even though the absence of publicly accessible information on such procedures prevents the use of this criterion.

The “business in difficulty” criterion is typically evaluated based on the financial statements of the most recent closed financial year, as published by the NBB. This criterion will be assessed using the figures as of December 31$^{\text{st}}$, 2019, prior to the onset of the Covid-19 pandemic, irrespective of the grant date. The mathematical representation of the financial stability condition is as follows:

$$\text{Financial Stability} \Leftrightarrow \begin{cases} \text{Equity}_t \geq \frac{1}{2} I \\ L_t \leq \frac{1}{4} I, \end{cases}$$

where Equity_t represents the equity of the business at the end of the last closed financial year, I the business issued capital, and L_t represents the capital loss in the last 12 months.

All sectors of activity are eligible (production, transformation, crafts, trade, services to businesses/people, construction, HORECA, etc.), with the exception of certain sectors such as banking, finance, insurance (except multi-brand insurance brokers), real estate promotion, production and/or distribution of energy or water (except the production of energy from renewable energy sources or quality cogeneration), education and training, culture (except audiovisual production), primary production of agricultural products listed in Annex I of the Treaty establishing the European Community, fishing, aquaculture, road freight transport for third parties (only when the financing concerns the acquisition of one or more road freight transport vehicles), shipbuilding, and the production, processing, and marketing of tobacco and tobacco products. As for the sectors that are not eligible for the loan, the information can be succinctly summarised in table 2.3, which utilises the first two digits of the NACE code sourced from BEL-First. The mathematical representation of the business sector condition is

$$\text{Eligibility of sector S} \Leftrightarrow S \notin E,$$

where S represents the business' activity sector, and E the set of excluded sectors.

Activity Sector	**NACE Code**
Banking, finance, insurance	64, 65, 66
Real estate promotion	68
Production and/or distribution of energy or water, except for the production of energy from renewable energy sources or quality co-generation	35, 36
Teaching and training	85
Culture, except for audiovisual production	90, 91
Production of cinematographic films, television films, other films	59
Primary production of agricultural products listed in Annex I to the Treaty establishing the European Community	01
Fishing	03
Aquaculture	03
Road freight transport for third parties, only when financing concerns the acquisition of one (or more) road freight transport vehicle(s)	49
Shipbuilding	30
Production, processing and marketing of tobacco and tobacco products	12

Table 2.3: The 2018 NACE codes for excluded sectors.

The eligibility criteria for the "Ricochet-recovery" loan are thus based on two primary conditions. Firstly, the company must be a SME that employs fewer than 50 people and has an annual turnover or total annual balance sheet that does not exceed EUR 10 million, with its operational headquarters established in Wallonia. Secondly, the company must demonstrate financial stability and operate in a sector different from those listed in table 2.3. If a company meets these conditions, it is considered eligible for the "Ricochet-recovery" loan.

The "Ricochet-recovery" loan is a particularly intriguing subject of study due to its unique blend of financial support mechanisms, which have been specifically tailored to address the challenges posed by the Covid-19 pandemic. In contrast to other financial products, the "Ricochet-recovery" loan combines a bank loan with a subordinate loan from SOCAMUT, thereby providing a comprehensive solution that addresses both immediate liquidity needs and long-term financial stability. This dual-component structure, along with the flexibility of options such as new loans, moratoriums, and combinations thereof, distinguishing it apart from other financial interventions.

Moreover, the "Ricochet-recovery" loan design, which includes government-backed guarantees and zero-interest rates, makes it more accessible and less risky for businesses to repay their debts. This accessibility is crucial for SMEs that often struggle to secure credit during economic downturns. By focusing on this specific loan, researchers can gain deeper insights into the effectiveness of such innovative financial products in improving credit access and supporting business recovery. This knowledge can inform the development of future financial instruments and policies aimed at enhancing economic resilience and stability.

2.2 Literature Review

SMEs' restricted access to finances and financing decisions frequently impede their ability to develop. Research has repeatedly demonstrated that SMEs have particular difficulties when it comes to capital structure and financing availability. Unlike larger firms, SMEs rely heavily on bank loans due to factors such as asymmetric information, limited credit history, and restricted access to alternative financing sources Franquesa and Vera, 2021. Their reliance on internal funding further hinders their growth, limiting their ability to capitalise on opportunities.

Asymmetric information, where lenders have less information about the borrower's creditworthiness, often leads to higher interest rates and stricter lending conditions Heyman et al., 2008. This issue is further exacerbated by the limited credit history of many SMEs, which makes it difficult for lenders to assess their profile accurately Rossi, 2017. The lack of collateral that SMEs can offer further compounds these challenges. Collateral is a critical factor in securing loans, as it provides lenders with a form of security in case of default. However, many SMEs lack substantial assets that can be used as collateral, making it even more difficult for them to obtain necessary funding Heyman et al., 2008.

High transaction costs associated with processing small loans also deter banks from lending to SMEs. These costs include the administrative expenses of evaluating loan applications, monitoring borrowers, and managing loan repayments. For banks, the cost of processing a small loan is often not significantly lower than that of processing a larger loan, making small loans less attractive from a profitability standpoint. This issue is further compounded by the higher risk associated with lending to SMEs, which often have less stable cash flows and higher default rates compared to larger firms. As a result, many banks are reluctant to lend to SMEs, leaving these enterprises in a precarious financial position and limiting their ability to grow and expand Organisation for Economic Co-operation and Development, 2022.

Relying on internal funds and informal financing sources presents another major obstacle for SMEs seeking to grow. Literature consistently highlights that SMEs' growth is significantly constrained by the availability of internal finance, particularly for those with limited access to external capital. Companies that rely heavily on their internal funds face growth constraints, limiting their ability to capitalise on opportunities. Improving access to external finance and developing alternative financing sources, such as venture capital and crowdfunding, are essential for fostering a more inclusive and dynamic business environment for SMEs Carpenter and Petersen, 2002; Fazzari et al., 1987.

Government policies have played a crucial role in improving access to finance for SMEs. By implementing measures such as subsidised loans, credit guarantees, and direct financial support, governments have created a more favourable environment for SMEs to secure the necessary funding for their operations and growth. These policies not only reduce the financial burden on SMEs but also encourage banks to lend to these entities by mitigating potential risks. Additionally, government-backed initiatives, such as grants and subsidies, provide SMEs with the capital needed to invest in innovation, expand their businesses, and contribute to economic development (FPS, n.d.-a, n.d.-b).

The integration of banks within the European Union (EU) has further bolstered access to finance for SMEs. The harmonisation of banking regulations across EU member states has facilitated cross-border banking and financial services, leading to increased competition among banks. This competition has resulted in better financial products and services for SMEs, including more favourable loan terms and interest rates. Moreover, the standardised regulatory framework within the EU has made it easier for SMEs to navigate the financial landscape and access funding from various sources. As a result, the combined efforts of government policies and EU banking integration have significantly improved the financial accessibility and stability for SMEs, fostering a more resilient and dynamic business environment (Moscalu et al., 2019).

While government policies and integration of banks within the EU have significantly improved access to finance for SMEs, crises like the 2008 global financial crisis and the Covid-19 pandemic highlight the inherent risk aversion of banks. During said global financial crisis, banks became highly risk-averse due to increased loan defaults, liquidity shortages, and stricter regulatory pressures. This led to a significant reduction in credit availability for SMEs (Harrison et al., 2022). Similarly, the Covid-19 pandemic exacerbated challenges for these entities as economic uncertainty and operational disruptions made banks more cautious in lending. During such periods, once again, additional government interventions are crucial to ensure that SMEs continue to receive the necessary financial support (Çolak and Öztekin, 2021).

In response to the global pandemic caused by the novel coronavirus, the Belgian government enacted a series of policies aimed at enhancing the resilience of SMEs and addressing the liquidity challenges they faced. These measures encompassed the provision of emergency loans, the deferment of payments, and the allocation of direct financial support. Notably, the Belgian government introduced the "Ricochet-recovery" loan, which offered smaller loans at a 0% interest rate to aid SMEs in managing their cash flow and working capital needs. Additionally, the government implemented deferred payment options to mitigate the financial burden on businesses. These policies proved effective in mitigating the adverse effects of the pandemic, as evidenced by the reduction in the number of bankruptcies during this period (OECD, 2020, 2022).

While these policies provided much-needed financial relief and helped reduce the number of bankruptcies for SMEs, their impact on credit access remains uncertain. As the Belgian economy began to recover, SMEs continued to face challenges in securing funding and credit due to the lasting impact of the pandemic. The temporary nature of these policies means that SMEs may still struggle to access the necessary financial resources to sustain and grow their businesses in the short term (Commision, 2024).

This master thesis aims to investigate whether the “Ricochet-recovery” loan has enhanced credit access for eligible firms compared to non-eligible ones. By analysing the credit access of SMEs that may have benefited from government interventions during the pandemic, this study seeks to provide valuable insights into the causal relationship between these policies and their effects on borrowing costs. The "Ricochet-recovery" loan, introduced in response to the economic challenges posed by the pandemic, is designed to support businesses in maintaining liquidity and continuing operations during periods of financial uncertainty.

The "Ricochet-recovery" loan, despite its 0% interest rate, can significantly influence the perceived risk of the firms that received it. If lenders view these firms as less risky due to the support they received, it could lead to a reduction in the credit spread (the difference between the interest rates on loans to these firms and the risk-free rate). Although the loan itself has no direct borrowing cost, it can indirectly affect the borrowing costs of eligible firms by facilitating their access to additional credit at lower interest rates. Therefore, studying the impact of the "Ricochet-recovery" loan on borrowing costs is pertinent, as the loan can influence the perceived risk of eligible firms and, consequently, their overall credit spread and access to additional funding.

Several studies have utilised credit spread as a proxy for perceived risk and borrowing costs. For instance, Caldara and Herbst, 2016 explored the interaction between monetary policy, financial markets, and the real economy, discovering that monetary policy shocks significantly influence fluctuations in industrial output and corporate credit spreads. Similarly, Akinci and Queralto, 2022 examined the behaviour of credit spreads during financial crises and highlighted the role of macro-prudential policy in mitigating these crises. Faust et al., 2011 emphasised the importance of credit spreads as predictors by using Bayesian Model Averaging to forecast real-time economic activity.

In addition, Gilchrist et al., 2014 analysed the impact of uncertainty and financial frictions on investment dynamics. They found that credit spreads play a crucial role in investment decisions, as lower implied borrowing costs provide better access to credit, thereby facilitating increased investments. Kaviani et al., 2020 investigated the effect of policy uncertainty on corporate credit spreads, demonstrating that policy uncertainty significantly impacts borrowing costs. Cesa-Bianchi, n.d. further explored the heterogeneous effects of monetary policy on firms, showing that credit spreads are a key measure of borrowing costs.

Notably, one study closely aligns with the intended research for this master thesis, conducted by Kim, 2023. Kim's study on government-backed financing in Korea after 2017 found that borrowing costs decreased more for firms eligible for government loans relative to ineligible firms. This led to larger post-policy increases in investment for eligible firms with higher pre-policy borrowing costs, while also decreasing the exit rate of low-productivity eligible firms.

To match the context of the research, the credit spread defined by Jihyun Kim will be used, which is the deviation of interest rates paid by a specific firm from the Belgian corporate bond yield (3-year, AA-) instead of the Korean corporate bond yield. The firm-specific interest rates are calculated using the total amount of debt and the total amount of interest expenses paid for a specific year. A decrease in the credit spread indicates lower borrowing costs, thus improving access to credit.

Drawing on Kim's findings, the study attempts to investigate if the "Ricochet-recovery" loan improves credit availability and lowers borrowing costs for Belgian eligible businesses. The fundamental mechanics of government-backed funding and its effect on credit spreads offer a useful comparative framework, notwithstanding the contextual variations between the two nations.

Furthermore, a DiD approach will be employed to isolate the effect of the "Ricochet-recovery" loan on credit access and borrowing costs. By comparing the changes in credit access and borrowing costs for eligible and non-eligible firms before and after the implementation of the policy, the causal impact of the "Ricochet-recovery" loan can be identified. This methodology will help control for other factors that may influence credit access and borrowing costs, ensuring that the observed effects are attributable to the policy intervention.

The DiD method is a widely used approach in impact evaluation studies across various disciplines. The book called the Effect provide a comprehensive overview of the DiD method, detailing its main assumptions, potential pitfalls, and its intuitive appeal for application in non-experimental settings such as policy evaluations. They illustrate the method with examples from the literature, highlighting its robustness and versatility (Huntington-Klein, 2022).

3 Methodology

The methodology section outlines the comprehensive approach taken to investigate the impact of the "Ricochet-recovery" loan on SMEs' borrowing costs. This section is divided into two main parts: models and data. The models employed in this study closely follow the framework established by Jihyun Kim, focusing on the impact of policy interventions on borrowing costs. By leveraging a similar methodological approach, this study aims to provide a thorough understanding of how the "Ricochet-recovery" loan influences the financial landscape for SMEs. The models incorporates various financial indicators and control variables to ensure robustness and accuracy. This structured approach ensures that the findings are grounded in established methodologies and provide meaningful insights (Kim, 2023).

The data section details the comprehensive data processing methodology, encompassing initial data collection through to final visualisation. The process begins with the collection of raw data from diverse sources, establishing the foundation for subsequent analysis. This is followed by a data cleansing phase, wherein errors and inconsistencies are rectified to ensure the dataset's integrity. Post data cleansing, the data processing phase involves essential calculations and transformations to prepare the data for meaningful analysis. Preliminary data visualisation is then employed to identify patterns and trends within the dataset. Subsequently, data filtering is conducted to select relevant data for further analysis, ensuring that only pertinent information is considered. Finally, the filtered data undergoes data modelling, where analytical models are constructed to extract valuable insights, culminating in the final visualisation that presents a clear summary of the results.

The model and data sections are an integral part of the methodology and provide a detailed roadmap for the study. The models section focuses on the theoretical framework and the specific models used to analyse the data. It includes a discussion of the variables, control measures, and the rationale behind the chosen models. Conversely, the data section provides a step-by-step guide to the data processing phases, ensuring transparency and reproducibility. Together, these sections form a sound methodology that underpins the results and conclusions of the study.

3.1 Models

Numerous studies have used credit spread as an indicator of perceived risk and borrowing costs. Nevertheless, it remains to be seen whether the policy in question will have a positive impact, as observed by Jihyun Kim in her study. In the aforementioned study, the author demonstrated that the Korean government's policy interventions have indeed resulted in an improvement in risk perception, subsequently leading to a reduction in borrowing costs. Specifically, Kim's study of government-backed financing in Korea post-2017 revealed that the reduction in borrowing costs was more pronounced for companies eligible for government loans compared to those that were not. This resulted in a greater increase in post-policy investment for eligible firms with higher pre-policy borrowing costs, while also reducing the exit rate for low-productivity eligible firms (Kim, 2023).

Due to the similarity of the research objective, which is to examine the impact of policy interventions on SMEs' borrowing costs, the models used will closely follow the framework established by Jihyun Kim. Specifically, by analysing the spread, an indicator of perceived risks and, consequently, borrowing costs, it can be determined whether the "Ricochet-recovery" loan has enabled SMEs to improve their access to external financing.

The focus herein is exclusively on borrowing costs. To guarantee robustness and accuracy, the models used by Jihyun Kim to study external financing costs include various financial indicators and control variables. Using a similar methodological approach, the intention is to provide a comprehensive understanding of how the "Ricochet-recovery" loan influences the financial landscape of SMEs. It has the potential to reduce their borrowing costs and improve their financial stability.

To match the context, the model was modified by removing the year 2019 instead of the year before the loan in 2016. In addition, instead of studying the effect on large companies and SMEs, the focus is solely on SMEs. Eligible SMEs are designated as the treatment group, while non-eligible SMEs serve as the control group, as previously defined. This allows for a comparison of similar groups based on SME criteria, such as the number of employees and financial criteria based on balance sheet and turnover.

The model used is called DiD model and it is a statistical technique that estimates the causal effect of a treatment by comparing changes in outcomes over time between a treatment group and a control group. This model is particularly suitable for this study as it allows for the comparison of borrowing costs before and after the implementation of the "Ricochet-recovery" loan, while controlling for other factors that might influence borrowing costs. There are two main models: the first assesses whether the spread is influenced by the treatment during the policy, and the second explores if increased government loans affect the sensitivity of credit spreads to firms' debt ratios, depending on eligibility.

3.1.1 Model 1: Policy Impact on Credit Spread

The objective of the first model, which employs a two-way fixed effects approach, is to determine whether the dependent variable (spread) is influenced by the eligibility of SMEs. This ensures that the policy affects borrowing costs. The β^k coefficients, representing the difference in the spread gap between eligible and non-eligible SMEs, will be closely examined to see if they are significantly different from zero. If they are, it indicates a significant impact of the policy intervention. The two-way fixed effects model is based on DiD methodology, which controls for unobserved heterogeneity by including fixed effects for both the time period and the cross-sectional units (i.e., entities). This approach helps to isolate the impact of the "Ricochet-recovery" loan on the credit spread by accounting for factors that are constant within each time period and each cross-sectional unit. This is represented by equation (3.1). The corresponding variables are summarised in table 3.1.

$$\text{Spread}_{i,s,t} = \beta^k E_{i,s} \times \text{After}_t + \gamma^x X_{i,s,t-1} + \alpha_i + \delta_t + \epsilon_{i,s,t} \tag{3.1}$$

The DiD assumption relies on parallel trends, which means that, in the absence of the treatment ("Ricochet-recovery" loan), the difference in outcomes (credit spreads) between the treatment group (eligible firms) and the control group (non-eligible firms) would have remained constant

Mathematical Sign	**Description**	**Definition**
$\text{Spread}_{i,s,t}$	Credit spread for firm i in sector s for year t	The difference between the yield on a corporate bond and a government bond of similar maturity, reflecting the perceived risk of the firm.
Year_k	Dummy variable for year k	A binary variable that takes the value 1 for year k and 0 otherwise, with the year 2019 excluded.
$\text{E}_{i,s}$	Indicator for "Ricochet-recovery" loan eligibility	A binary variable that takes the value 1 if firm i in sector s is eligible for the "Ricochet-recovery" loan, and 0 otherwise.
After_t	Dummy variable for post-policy period	A binary variable that takes the value 1 for the period after the policy implementation, and 0 otherwise.
$\text{X}_{i,s,t-1}$	Firm-specific control variables	A vector of control variables including: - Equity to asset ratio - Debt to asset ratio - Cash to asset ratio - Operational profit to asset ratio
α_i	Entity fixed effects	Fixed effects that control for unobserved heterogeneity at the entity level.
δ_t	Time fixed effects	Fixed effects that control for unobserved heterogeneity at the time level.
$\epsilon_{i,s,t}$	Error term	The residual term capturing unexplained variation in the model.

Table 3.1: Definitions of variables in the two-way fixed effects model.

over time. This assumption is crucial for the validity of the DiD model, as it ensures that the observed treatment effect is not driven by pre-existing differences between the treatment and control groups. If this assumption does not hold, the DiD model may yield biased results, leading to incorrect conclusions about the policy's impact.

Verifying the parallel trends assumption is hence a critical step in the analysis. Without this verification, the reliability of the estimated treatment effect ($E_{i,s} \times \text{After}_t$) would be questionable. Ensuring that the parallel trends assumption holds helps to establish the credibility of the findings. Although the parallel trends assumption cannot be definitively proven, ensuring its plausibility helps to establish the credibility of the findings. Definitive proof or testing of parallel trends is not possible, but two tests can provide some evidence to make parallel trends appear more plausible as an assumption. These tests are the test of long-term effects and the placebo test.

An efficient way of assessing the parallel trends hypothesis is to study the long-term effects using trend analysis. This consists of reviewing the trends in credit spreads for the treatment group and the control group before and after the implementation of the "Ricochet-recovery" loan, while excluding the year immediately preceding the application of the policy. The reason for this exclusion is to ensure that anticipation effects are not mixed with the actual impact of the policy. Although the parallel trends hypothesis cannot be definitively proven, analysis of long-term effects can provide evidence of its plausibility (Huntington-Klein, 2022). The long-term effects model is represented by equation (3.2), and the corresponding variables are summarised in table 3.1.

$$\text{Spread}_{i,s,t} = \sum_{k \neq 2019} \beta^k \text{Year}_k E_{i,s} + \gamma^x X_{i,s,t-1} + \alpha_i + \delta_t + \epsilon_{i,s,t} \tag{3.2}$$

If the trends in credit spreads are close to zero before the policy implementation, it indicates that the policy had no effect prior to its enactment, thereby supporting the evidence of parallel trends assumption. This assumption is crucial for the validity of the DiD model, as it ensures that the observed treatment effect is not driven by pre-existing differences between the treatment and control groups. Conversely, if the trends are not close to zero, the validity of the DiD model may be compromised, suggesting that the estimated treatment effect may be biased. This would imply that other factors, rather than the policy, are driving the observed changes in credit spreads.

The long-term effects model can further investigate whether the spread for eligible firms decreased relative to non-eligible firms following the policy change. This analysis involves re-examining the β^k coefficient, which represents the difference in the rate differential between eligible and non-eligible companies, albeit this time for a given year relative to 2019. A significant negative β^k coefficient would indicate that the policy effectively reduced the credit spread for eligible firms. This reduction in credit spread would suggest that the "Ricochet-recovery" loan successfully lowered borrowing costs for eligible firms. Understanding this impact is essential for evaluating the policy's effectiveness.

By examining the β^k coefficients, the extent to which the "Ricochet-recovery" loan influenced the borrowing costs of eligible firms compared to non-eligible firms can be determined. This analysis provides valuable insights into the policy's impact on financial markets. A significant negative β^k coefficient would confirm that the policy had a beneficial effect on eligible firms. Conversely, if the β^k coefficients are not significant, it would suggest that the policy did not have the intended impact.

Another method that can provide some evidence of parallel trends, often referred to as a robustness check, is a placebo test. A placebo test involves applying the same DiD model to a period before the actual treatment was implemented or to a different outcome that should not be affected by the treatment. If the placebo test shows no significant effect, it provides further confidence in the validity of the original DiD model. Conversely, if the placebo test shows a significant effect, it suggests that the original results may be driven by factors other than the treatment.

The same DiD model, specifically the two-way fixed effects model represented by equation (3.1), was applied to periods before the actual treatment was implemented. Two equations were created, each with a different fake treatment period. The first equation uses 2017 as the fake treatment period, meaning that the variable Before_t represents the year 2017. The second equation uses 2018 as the fake treatment period, meaning that Before_t includes both 2017 and 2018. If the parallel trends assumption holds, the fake treatment variables in both equations should be statistically insignificant. This approach helps to verify the plausibility of the parallel trends assumption. By using fake treatment periods, it is possible to check for any pre-existing trends that might affect the results. If the fake treatment variables are insignificant, it provides further confidence in the validity of the original DiD model.

The process to evaluate the policy impact on credit spread can be summarised by the figure 3.1. It begins with dividing the final dataset into treatment (eligible firms) and control (non-eligible firms) groups. A two-way fixed effects model is then applied to control for unobserved heterogeneity. Long-term effects are examined by analysing trends in credit spreads before and after the policy, excluding the year immediately preceding it to avoid anticipation effects. Lastly, placebo tests are conducted to ensure robustness by applying the model to periods before the actual treatment or to different unaffected outcomes. The parallel trends assumption is crucial, ensuring that the difference in credit spreads between the groups would have remained constant over time without the policy. This comprehensive approach helps verify the assumption's plausibility and establish the findings' credibility.

3.1.2 Model 2: Eligibility-Dependent Sensitivity of Credit Spreads to Indebtedness

Once the effect of policy on credit spreads has been confirmed, the next step is to examine whether the increase in government loans has changed the sensitivity of credit spreads to firms' debt levels. Then examines whether this change varies according to eligibility. The sensitivity of credit spreads to corporate debt is the extent to which credit spreads react to changes in a company's debt level. Understanding this sensitivity is essential for assessing the risk associated with lending to different companies, and therefore the risk perceived by lenders. Through this analysis, it's possible to determine whether the policy had a significant impact on eligible and non-eligible companies.

As previously defined, credit spread is the difference in yield between a corporate bond and a comparable government bond, reflecting the additional risk investors take on when lending to a corporation. Indebtedness, on the other hand, is the amount of debt a firm has. When a firm increases its debt, it typically becomes riskier due to higher obligations, which can affect its ability to repay loans. Sensitivity means the extent to which credit spreads widen or narrow in response to changes in the firm's debt levels. Therefore, high sensitivity indicates that even small increases in debt can lead to significant widening of credit spreads, while low sensitivity means that changes in indebtedness have a smaller impact on credit spreads.

To conduct this analysis, the period is divided into two sub-periods: before (2017-2019) and after (2020-2022). This division allows for a clear comparison of the effects before and after the policy implementation. By examining these sub-periods, it is possible to identify any shifts in the relationship between credit spreads and firms' indebtedness. The analysis will

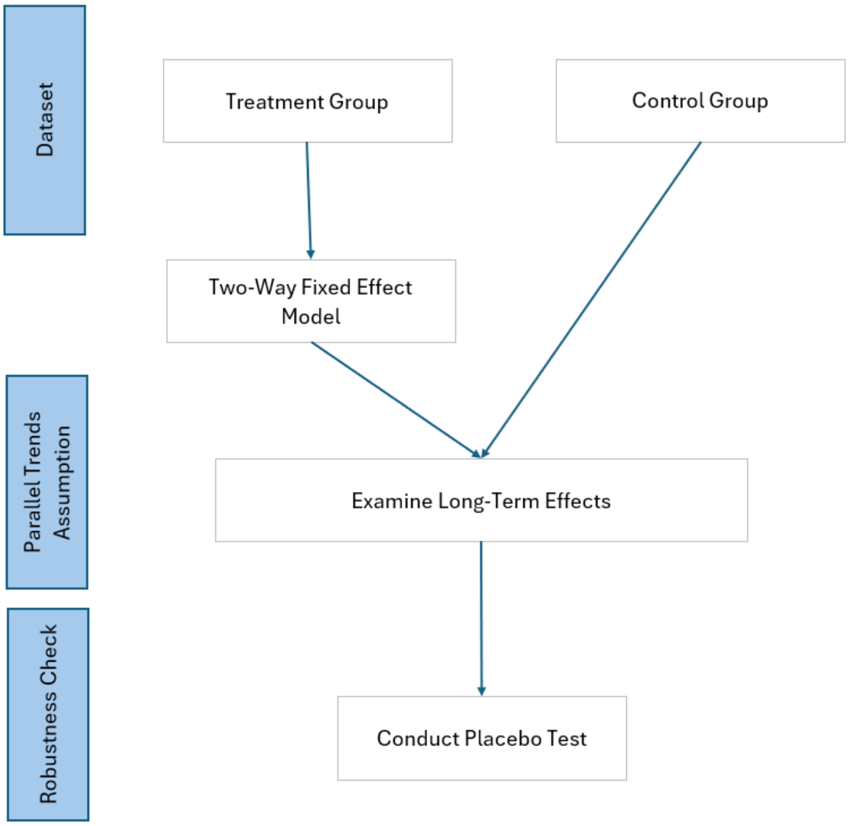

Figure 3.1: Process for evaluating the policy impact on credit spread.

focus on determining if eligible firms experienced a different change in sensitivity compared to non-eligible firms. The model study is represented by equation (3.3) and the relevant variables are summarised in the table 3.2.

$$\begin{aligned}\text{Spread}_{i,s,t} =& \beta_0 \text{Debt Ratio}_{i,s,t-1} + \beta_1 E_{i,s} \text{Debt Ratio}_{i,s,t-1} \\ &+ \beta_2 \text{Debt Ratio}_{i,s,t-1} \text{After}_t \\ &+ \beta_3 E_{i,s} \text{Debt Ratio}_{i,s,t-1} \text{After}_t \\ &+ \gamma^x X_{i,s,t-1} + \gamma_{s;t} + \epsilon_{i,s,t}\end{aligned} \tag{3.3}$$

Mathematical Sign	Description	Definition
$\text{Spread}_{i,s,t}$	Credit spread for firm i in sector s for year t	The difference between the yield on a corporate bond and a government bond of similar maturity, reflecting the perceived risk of the firm.
$\text{Debt Ratio}_{i,s,t-1}$	Debt to asset ratio for firm i in sector s for year $t-1$	The ratio of a firm's total debt to its total assets, indicating the firm's leverage.
$E_{i,s}$	Indicator for SME eligibility	A binary variable that takes the value 1 if firm i in sector s is eligible as an SME, and 0 otherwise.
After_t	Dummy variable for post-policy period	A binary variable that takes the value 1 for the period after the policy implementation, and 0 otherwise.
$X_{i,s,t-1}$	Firm-specific control variables	A vector of control variables including: - Equity to asset ratio - Cash to asset ratio - Operational profit to asset ratio
$\gamma_{s,t}$	Sector-year interacted fixed effects	Fixed effects that control for unobserved heterogeneity at the sector-year level.
$\epsilon_{i,s,t}$	Error term	The residual term capturing unexplained variation in the model.

Table 3.2: Definitions of variables in the long-term fixed effects model.

3.2 Data

The following section describes the complete data processing process, from initial data collection to final visualisation. The process begins with data collection, where raw data is gathered from a variety of sources, laying the foundations for subsequent analysis. A subsequent data cleansing phase is then undertaken to ensure the integrity of the dataset by rectifying errors and inconsistencies.

Once data cleansing has been completed, the data processing phase is launched, involving essential calculations and transformations. This stage is crucial, as it prepares data for meaningful analysis by calculating variables, aggregating data and applying the necessary transformations. As a preliminary insight, data visualisation is used, making it easier to identify patterns and trends within the dataset.

The process then leads to the data filtering phase, during which relevant data are selected for further analysis, ensuring that only relevant information is taken into account. The filtered data is then subjected to data modelling, in which analytical models are built to extract information. The final stage involves the final visualisation, which presents a clear and concise summary of the results.

Figure 3.2 below illustrates the entire process, highlighting the interconnected stages and their respective roles in transforming raw data into valuable information. By adhering to this structured approach, reliable analysis is guaranteed.

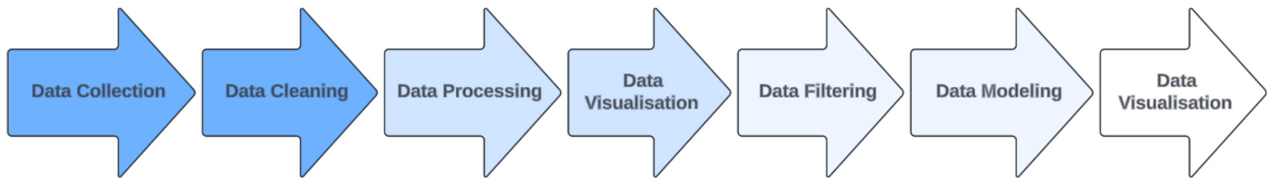

Figure 3.2: Schematic diagram of the data process.

3.2.1 Data Collection and Cleaning

The data for this study is sourced from the Bel-first database, a detailed database that offers information on companies in Belgium and Luxembourg. This database encompasses firms with various legal statuses, including active companies, those in provisional legal situations, and those with unknown statuses. It provides historical financial data, enabling longitudinal studies and trend analysis over time. Additionally, it includes sector-specific data, which is useful for examining sector eligibility, for instance.

The Bel-first database has been widely used in academic research (van Dijk, 2024). For example, a study of the debt policies evolution by Belgian researchers utilised it to analyse the financial performance of Belgian companies over a fifteen-year period (Hanssens et al., 2016). Another study examined the impact of user-generated reviews on the financial performance of restaurants in Belgium, using firm-level data from Bel-first (Abdullah et al., 2022). These studies highlight the robustness and reliability of the Bel-first database in providing detailed financial information for academic research.

In terms of this master thesis, the selection criteria for the dataset encompass several financial and operational metrics over a span of seven years. These metrics include the number of employees, turnover, total assets, non-current liabilities, current liabilities, tangible assets, financial debts, cash and cash equivalents, cash at bank and in hand, shareholders' funds, gross profit, operating profit/loss, interest cover, Earnings Before Interest and Taxes (EBIT), and profit/loss for the period after taxes. The data is collected for the last available year and the six preceding years, with a preference for unconsolidated accounts and the exclusion of non-reporting firms (NRF).

To ensure the relevance and accuracy of the data, the study focuses on companies with fewer than 50 employees and a turnover and total assets of less than EUR 10 million. Financial metrics are employed to analyse the impact of the "Ricochet-recovery" loan on credit access and borrowing costs. By examining these variables over multiple years, the study aims to capture the longitudinal effects of the loan program. Additionally, the data is filtered to include only companies from the Walloon Region, providing a regional context to the analysis. This comprehensive dataset allows for a robust examination of the financial health and credit dynamics of the firms, specifically SMEs, under study.

Based on the selection criteria summarised in table 3.3, the dataset includes 17,688 firms. Due to importation limitations with Bel-first, the data for these firms was exported in four CSV files. It is important to note that the values beside each search category in table 3.3 represent the number of firms with available information over the specified years. And some search categories and metrics values will not be utilised in this master thesis due to time constraints, the dataset remains sufficiently large to support the current study and potentially serve as a resource for future research or master theses.

Category	**Value**
1. Legal status: Active companies, File in a provisional legal situation, Unknown	2,351,443
2. Number of Employees: max=50	293,988
3. Turnover, using estimates (th EUR): max=10,000	316,606
4. Total assets (th EUR): max=10,000	376,677
5. NON CURRENT LIABILITIES	223,402
6. CURRENT LIABILITIES	399,825
7. Tangible assets	289,222
8. Financial debts	186,477
9. Cash & cash equivalent	380,400
10. Cash at bank and in hand	324,589
11. Shareholders funds / Social funds	412,848
12. Gross Profit	341,853
13. Operating P/L	372,944
14. Interest cover (x)	287,168
15. EBIT	373,138
16. Region, province, subregion & town: Walloon Region	863,272
17. P/L for the period after taxes (+/-)	373,011
Boolean search: 1 And 2 And (3 Or 4) And 5 And 6 And 7 And 8 And 9 And 10 And 11 And 12 And 13 And 14 And 15 And 16 And 17 TOTAL	17,688

Table 3.3: Search summary of financial metrics and categories for last available year and the six preceding years from Bel-First.

The preliminary data cleaning process was conducted using Python, with a particular focus on the Pandas library. Python is widely recognised as an optimal programming language due to its simplicity, readability, and extensive library support. Its intuitive syntax facilitates ease of use for both novice and experienced programmers. Among the numerous libraries available, Pandas stands out for its robust capabilities in data manipulation and analysis. It provides efficient data structures, such as DataFrames, which are essential for handling large datasets. The comprehensive functionality of Pandas encompasses data cleaning, transformation, and aggregation, which are critical for preparing data for subsequent analysis McKinney, 2010.

In this study, the data cleaning process involved removing missing values recorded as N.A, n.a, or 0. This step eliminated 66 rows related to Interest Cover (x), 3,123 rows associated with the Sum of Financial Debts in thousand EUR, and 218 rows pertaining to NACE BEL 2008, Primary Code(s), thereby reducing the dataset to 14,216 firms. Addressing these missing values was crucial, as Interest Cover (x) is needed for calculating total interest debt, the NACE BEL code is required for eligibility criteria, and the Sum of Financial Debts serves as the denominator in the calculation of the spread. By systematically refining the dataset, it became more manageable and analytically meaningful.

Bel-first utilises the last available year and year - x (where x is a positive integer) without specifying the actual year (e.g., 20XX) in their search categories. Consequently, the exact last available year is only determined after completing the search and examining the dataset. It is crucial to ensure that the final year available (Year - 6) is consistent and that the dataset begins from 2016. This process is akin to filtering the dataset based on the last available year indicated in a specific column when exporting the data.

The majority of companies, approximately 83.2%, have their most recent data available for the year 2022. In contrast, a smaller proportion of companies have their last available data in 2020, 2021, and 2023, collectively representing about 16.8% of the total number of companies with data available in 2022. Specifically, companies with their last available data in 2020, 2021, and 2023 account for approximately 0.71%, 1.58%, and 14.51%, respectively. This indicates that the data for the year 2022 is the most comprehensive and representative for the majority of companies. For practical purposes, the 16.8% of companies with data from other years were excluded.

Standard cleaning processes have also been implemented to ensure data quality. Specifically, any duplicate firms have been identified and removed to avoid redundancy. Additionally, values have been meticulously formatted to ensure consistency and accuracy across the dataset. Columns have been renamed to eliminate any instances of "\n" that may have appeared during the data import process. Furthermore, the format of the years has been adjusted to enhance clarity and readability. These steps are crucial for the following steps of the master thesis.

Then, the number of employees, total assets (as a proxy for the value of the balance sheet), and turnover were checked to ensure that only SMEs were studied. A total of 62 firms were found to have either equal to or more than 50 employees, or total assets and turnover equal to or exceeding EUR 10 million. Consequently, the dataset was further refined to comprise 12,013 firms. The information is summarised in the following table 3.4.

3.2.2 Data Processing

Bel-first is a practical resource for accessing the accounts of firms. However, when studying SMEs, there are notable challenges. Unlike larger firms or those with consolidated accounts, SMEs often lack detailed items in their balance sheets or profit and loss accounts. This absence of information presents a significant obstacle in conducting comprehensive analyses of SMEs.

Description	Number of Entries
Initial Dataset	15,734
After Initial Cleaning	12,327
Interest Cover (x)	66
Sum of Financial Debts (th EUR)	3,123
NACE BEL 2008, Primary Code(s)	218
After Removing Unconsolidated Accounts (2021)	176
After Removing Unconsolidated Accounts (2020)	76
Final Initial Dataset	12,075
After Removing Non-SMEs	62
Final Dataset	**12,013**

Table 3.4: Summary of dataset cleaning process.

To address this issue, several items were calculated manually including total liabilities, equity, interest expense, debt ratio and investment. Initially, the dataset comprised 115 columns. After calculating all these metrics for each year from 2016 to 2022, the number of columns increased to 157.

In finance, equity is the value of ownership in a company, calculated by subtracting liabilities from assets. It signifies the shareholders' interest in the company, giving them a claim to a share of the company's assets and earnings. As described in the previous section, equity is crucial for assessing a firm's financial stability in eligibility criteria. It was calculated using balance sheet principles, as illustrated by figure 3.3, from academic courses and textbooks (Ross et al., 2021). This involved deriving equity by subtracting total liabilities from total assets.

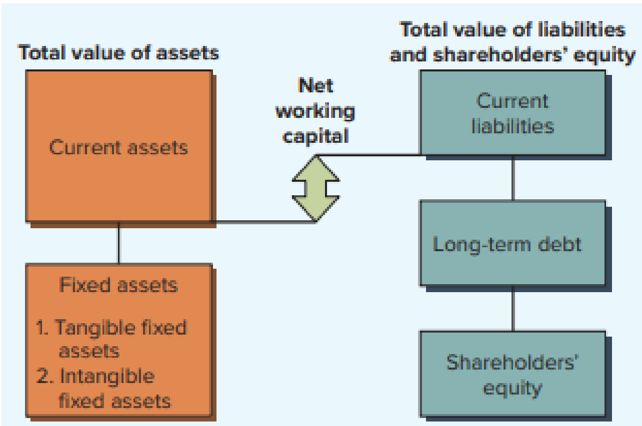

Figure 3.3: Overview of the balance sheet and its elements.
Image source: Fundamentals of Corporate Finance Ross et al., 2021.

First, the total liabilities of the firm were calculated, which include both current liabilities (short-term obligations) and non-current liabilities (long-term debts). The formula for total liabilities is as follows:

$$\text{Total Liabilities} = \text{Current Liabilities} + \text{Non Current Liabilities} \tag{3.4}$$

Once the total liabilities were established, equity was derived by subtracting these liabilities from the total assets of the firm. Total assets encompass all the resources owned by the firm, including cash, inventory, property, and equipment. The formula for calculating equity is:

$$\text{Equity} = \text{Total Assets} - \text{Total Liabilities} \tag{3.5}$$

Subsequently, using equation (3.4) to calculate total liabilities, the debt ratio was calculated. The debt ratio is defined as the total liabilities divided by the total assets and it measures the extent of a company's leverage. This metric will be used in the second model as independent variable.

$$\text{Debt Ratio} = \frac{\text{Total Liabilities}}{\text{Total Assets}} \tag{3.6}$$

Afterwards, investment is measured by examining the change in tangible assets between consecutive periods, offering a valuable measure of the average investment rate by companies from 2016 to 2022. According to the National Bureau of Economic Research (NBER) study, investment is closely tied to borrowing costs (Gilchrist et al., 2014). Although these links are beyond the scope of this study, average investment can generally indicate financial health and will be discussed in the results section. Further research could verify this relationship in the given context. The investment measure is calculated by taking twice the difference in tangible assets between periods t and $t-1$, and then dividing this value by the total tangible assets for the respective periods (t and $t-1$). This formula determines the rate of investment in tangible assets by considering twice the change in tangible assets (representing the investment) and dividing it by the total tangible assets, then multiplying the result by 100 to convert it into a percentage.

$$\text{Investment Rate} = \left(\frac{2 \times (\text{Tangible Asset}_t - \text{Tangible Asset}_{t-1})}{\text{Total Tangible Assets}} \right) \times 100 \tag{3.7}$$

Total interest expense is also not available in the Bel-first database for these entities, necessitating an alternative method to calculate it, if applicable. Interest expense represents the cost incurred by an entity for borrowed funds. They are calculated by dividing EBIT by the interest cover, where interest cover is defined as EBIT divided by interest expense. Therefore, dividing EBIT by the interest cover gives the interest expense, as shown by equation (3.8). This expense is useful when calculating the spread.

$$\text{Interest Expense} = \frac{EBIT}{\text{Interest Cover}} \tag{3.8}$$

After calculating the various financial metrics, variables for the models are required to be calculated. But first, SMEs are classified as either eligible or non-eligible based on the criteria outlined in chapter 2. Loan eligibility is determined by financial stability and sector of activity, evaluated through the business's financial accounts and its sector. While Kim's research included corporations and determined loan eligibility based on company size, allowing SMEs to qualify, this master's thesis uses different criteria. Therefore, the dummy variable 'SME' (1 for SMEs, 0 otherwise) will not be used. Instead, an indicator variable, E, is established: E is set to 1 if both Financial Stability (FS) and Sector of Activity (SA) criteria are met (FS=1 and SA=1). In all other cases, E is set to 0. Thus, a loan is considered eligible (E=1) only when both criteria are satisfied. If either criterion is not met, the loan is deemed ineligible ($E = 0$).

Then, the spread is calculated. It is determined as the difference between the interest ratio and the corporate bond rate (AA-3yr), serves as a crucial indicator of a firm's borrowing costs over the benchmark rate. This spread reflects the credit risk premium. It is the additional yield investors demand for taking on the risk of lending to a firm with an AA- credit rating, which spans from 2016 to 2022 Bonds, n.d. The Belgian corporate bond rate (AA- 2 yr.) is summarised in table 3.5.

$$
\begin{aligned}
\text{Spread}_{i,s,t} &= \left(\frac{2 \times \text{Interest}_t}{\text{Financial Debt}_t + \text{Financial Debt}_{t-1}}\right) \times 100 - \text{Belgian CBR (AA- 3yr)} \\
&= \text{Interest Ratio} - \text{Belgian CBR (AA- 3yr)}
\end{aligned}
\tag{3.9}
$$

In Kim's research, total debt is used to calculate the interest ratio. However, this master's thesis focuses on financial debt when investigating borrowing costs. This choice is due to its direct relevance to borrowing costs, its specificity in including only interest-incurring liabilities, and its accuracy in reflecting the true cost of borrowing. While total debt provides a broader view of a firm's indebtedness, financial debt offers a more precise measure for this specific research question. Additionally, financial debt values are available, whereas total debt values are not available in the Bel-First database.

	2016	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Belgian CBR (AA-3yr)	2.749	-0.61	-0.712	-0.568	-0.354	-0.438	-0.658

Table 3.5: Belgian corporate bond rates (AA-3yr) over the years.

After establishing the variables used in the two models, the vector of firm-specific controls is set using the following equations. The firm-specific controls are then shifted by one year to create lagged variables within each firm. These variables are:

- **Equity to Asset Ratio**:

$$\text{Equity to Asset Ratio (Lagged)} = \frac{\text{Total Equity}_{t-1}}{\text{Total Assets}_{t-1}} \tag{3.10}$$

- **Debt to Asset Ratio (Lagged)**:

$$\text{Debt to Asset Ratio (Lagged)} = \frac{\text{Total Debt}_{t-1}}{\text{Total Assets}_{t-1}} \tag{3.11}$$

- **Cash to Asset Ratio (Lagged)**:

$$\text{Cash to Asset Ratio (Lagged)} = \frac{\text{Cash and Cash Equivalents}_{t-1}}{\text{Total Assets}_{t-1}} \tag{3.12}$$

- **Operational Profit to Asset Ratio (Lagged)**:

$$\text{Operational Profit to Asset Ratio (Lagged)} = \frac{\text{Operational Profit}_{t-1}}{\text{Total Assets}_{t-1}} \tag{3.13}$$

3.2.3 Data Visualisation and Modelling

Data visualisation will be briefly mentioned, with a focus on the use of the Seaborn Waskom, 2021 and Matplotlib Hunter, 2007 packages. Using Seaborn and Matplotlib for data visualisation offers several advantages that enhance the efficiency and quality of the analysis. Matplotlib provides a comprehensive range of plotting functions, making it suitable for a variety of visualisation needs. Besides, its flexibility allows for detailed customisation of plots, enabling users to create highly tailored visual representations of their data. Additionally, it integrates well with other libraries, such as NumPy and Pandas, facilitating a smooth workflow Hunter, 2007.

On the other hand, Seaborn, built on top of Matplotlib, simplifies the creation of complex visualisations with minimal code, making it an ideal choice for efficient data visualisation. It offers built-in themes and colour palettes that enhance the visual appeal of the graphics, making them more informative and attractive Waskom, 2021. The seamless integration with Pandas DataFrames allows for easy visualisation of cleaned data, streamlining the entire data analysis process.

The visualisation process was conducted before the dataset filtering process and after the modelling phase using PanelOLS. Initially, the data was examined in general as part of the data description to identify any outliers or segments that needed to be excluded, such as sectors containing only non-eligible SMEs or, conversely, sectors with only eligible SMEs. This step ensured the consistency of the data prior to modelling. Following the modelling phase, the visualisation process was employed to illustrate the results of the model and to present the data after the exclusion of certain firms and values.

The initial step of dataset filtering process involves removing from consideration any sectors that exclusively contain companies of a single eligibility type, either eligible or non-eligible. This is crucial because the models being used are DiD, which compares the effect of a specific loan policy on eligible and non-eligible firms. If a sector only has one type of eligibility, it is not possible to perform the DiD analysis. By excluding these sectors, the analysis can accurately compare the effects of the loan policy across both types of firms, ensuring the validity and reliability of the results.

This step removes all sectors that exclusively contain non-eligible SMEs (see table 2.3, in chapter 2), ensuring that only eligible sectors are retained. Although this results in the exclusion of some non-eligible firms, the majority of non-eligible firms remain within the eligible sectors, as only 1322 firms are dropped. This is because non-eligible firms in eligible sectors are not financially stable, as defined by the financial stability criteria. By focusing on eligible sectors, the analysis can more accurately assess the impact of the loan policy on both eligible and non-eligible firms. This step therefore avoids biases that could arise from an unbalanced sample, leading to more reliable and valid conclusions.

All necessary columns for the spread models are localised, and a spread dataframe is created, encompassing all required variables (both dependent and independent) for the study. This ensures that all relevant data is consolidated in one place, facilitating easier analysis and manipulation. In this, step we have thus 10,691 row (firms) and 37 columns. The dataframe is then reshaped to ensure that each firm has a distinct row for each year, representing firm-year observations, rather than having a single row per firm with multiple columns for each year (e.g., Spread 2016, Spread 2017, etc.). This restructuring is crucial for longitudinal data analysis, as it allows for a more straightforward comparison of firm performance across different years. In this step, the dataset includes 74,837 firm-year observations ($10,691 \times 7$ years) and comprises 9 columns.

To ensure that all variables are different from zero, any zero values were identified and subsequently dropped. This step resulted in a dataset containing 73,680 firm-year observations. Following this, firm-year observations with missing data were identified and removed to preserve the longitudinal integrity of the study. This process led to the exclusion of 1,066 firms from the dataset. Consequently, the dataset was refined to include only those firms with complete data across all years. The final dataset comprised 67,375 firm-year observations.

Given the presence of lagged values from vector-specific controls, these lagged values are shifted to the subsequent year (e.g., the equity-to-asset ratio for 2016 is lagged into 2017). Subsequently, all 2016 values are dropped due to the absence of their lagged values from 2015. This is done to maintain consistency in the dataset, as including 2016 values without their corresponding lagged values from 2015 would result in incomplete data and potentially skew the analysis. Additionally, columns that are not lagged are removed to enhance the readability of the dataframe. This step simplifies the dataset, making it easier to interpret and analyse the remaining variables. The dataset, thus, drop to 57,750 firm-year observations.

Prior to conducting any modelling, a descriptive statistical analysis was performed. During this analysis, it was observed that the spread variable contained outlier values that could potentially skew the results. To facilitate a deeper understanding of the data, two graphs were created, as illustrated in figure 3.4. These graphs provide a comprehensive view of the distribution of the spread variable within the dataset.

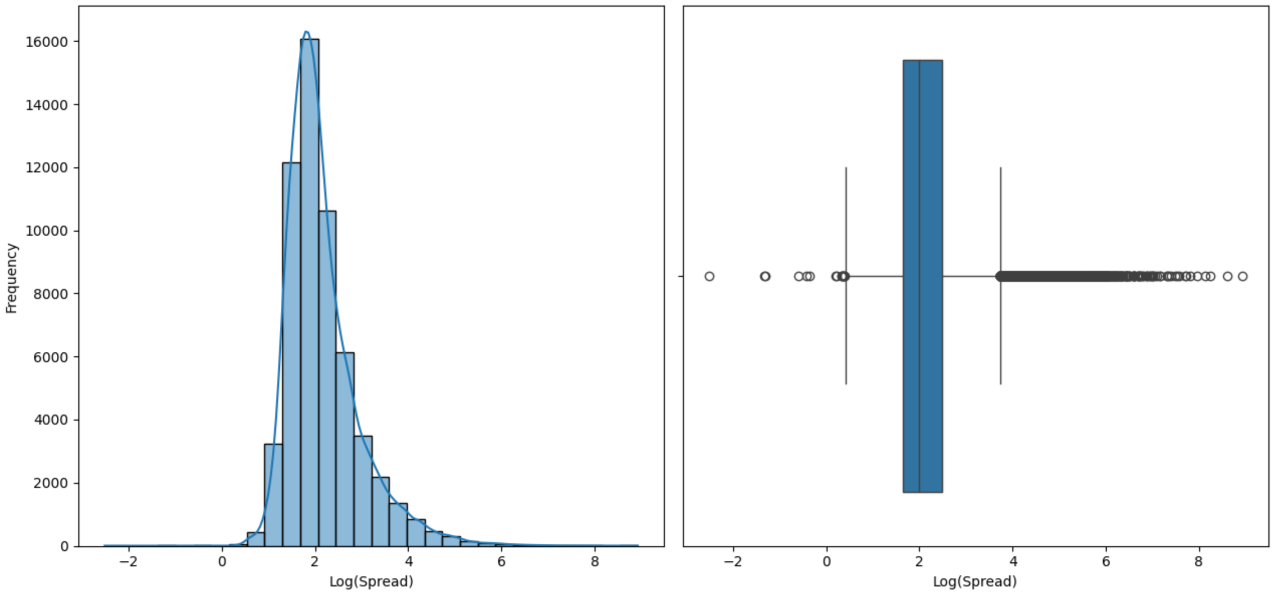

Figure 3.4: Distribution of spread variable before removing outliers.

The left graph, a histogram with a Kernel Density Estimate (KDE) overlay, illustrates the frequency distribution of the spread values on a logarithmic scale. The x-axis represents the logarithm of the spread values, while the y-axis indicates the frequency of these values. The majority of the data points are concentrated around the lower end of the scale, suggesting that most spread values are relatively small. The KDE overlay provides a smoothed curve that represents the probability density function of the spread values, highlighting the overall distribution pattern. Notably, the presence of a long tail on the right side of the histogram indicates the existence of some extreme high values, which are considered outliers.

Complementing the histogram, the box plot on the right of figure 3.5 provides a visual summary of the distribution of the spread values, emphasising the central tendency and variability. The central rectangle, known as the interquartile range (IQR), contains the middle 50% of the data, with the line inside the rectangle representing the median value. The whiskers extend to the minimum and maximum values within 1.5 times the IQR from the lower and upper quartiles, respectively. Any data points beyond the whiskers are considered outliers and are represented as individual dots. This box plot clearly shows the presence of several outliers on the higher end of the spread values, confirming the observations from the histogram.

Given these findings, it became evident that the spread variable contained outlier values. To address this issue and ensure the robustness of the analysis, all spread values above the 99th percentile were identified and subsequently removed from the dataset. This approach was taken to mitigate the influence of extreme values on statistical measures such as the mean and standard deviation, which can lead to misleading interpretations. By removing values above the 99th percentile, the impact of these extreme values is minimised, resulting in a more accurate and reliable analysis.

Following the removal of these extreme values, the figure 3.5 displays two graphs that illustrate the distribution of the spread variable. The histogram on the left now shows a more concentrated and symmetrical distribution of spread values, with the majority of data points clustered around the centre. The KDE overlay highlights the smoothed probability density function, indicating a more normalised distribution. The box plot on the right provides a visual summary of the central tendency and variability of the spread values. The IQR is clearly defined, with the median value represented by a line inside the box. The whiskers extend to the minimum and maximum values within 1.5 times the IQR, and a few individual points are still visible as outliers.

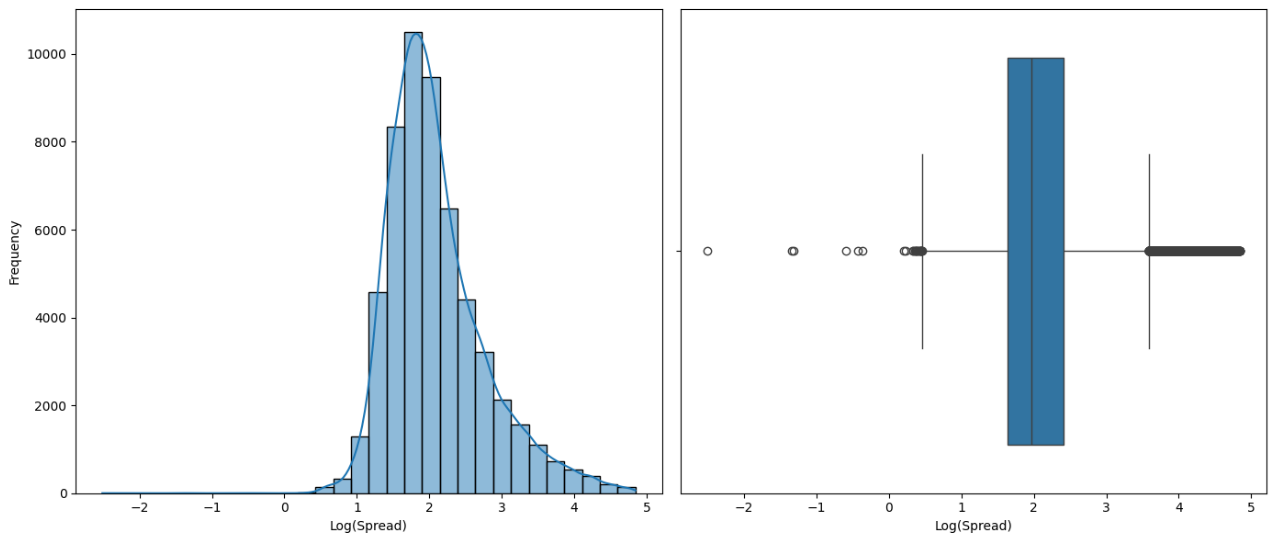

Figure 3.5: Distribution of spread variable after removing outliers above the 99th percentile.

The decision to drop only the values above the 99th percentile, rather than all outliers, was made to balance data integrity and robustness. While extreme outliers can skew the analysis and lead to misleading interpretations, not all outliers are necessarily erroneous or irrelevant. Some outliers may contain valuable information about the data's behaviour or indicate special cases worth investigating separately Leys et al., 2019. By removing only the most extreme values, the analysis becomes more accurate and reliable, while still preserving the dataset's overall richness and variability. This approach ensures a more robust and representative analysis without discarding potentially meaningful data points.

These steps can be called dataset filtering process and it involved several key steps to refine and prepare the data for analysis. Initially, the dataset comprised 12,013 firms. The first step was to filter for eligible sectors, reducing the number of firms to 10,691 and resulting in 74,837 firm-year observations over 7 years. Next, zero values were excluded, further reducing the number of firms to 9,625 and yielding 67,375 firm-year observations. The year 2016 was then removed, maintaining the number of firms at 9,625 but reducing the years covered to 6, with 57,750 firm-year observations. To address the issue of outliers, the top 99th percentile of the spread variable was excluded, resulting in 9,263 firms and 55,578 firm-year observations. The final refined dataset consists of 9,263 firms over 6 years, with 55,578 firm-year observations, ensuring a robust and accurate basis for subsequent analysis. This process is summarised in the table 3.6.

Operation	Firms Number	Δ	Years	Firm-Year Obs
Initial dataset	12,013	/	/	/
Filter eligible sectors	10,691	-1,322	7	74,837
Exclude zero values	9,625	-1,066	7	67,375
Remove year 2016	9,625	0	6	57,750
Exclude top 99th percentile spread	9,263	-362	6	55,578
Final dataset	9,263	0	6	55,578

Table 3.6: Summary of data filtering process.

After filtering the data, different models were conducted for the study. The choice was made to use PanelOLS instead of StatModels for all the models Sheppard et al., 2024; Seabold and Perktold, 2010. Both methods were tried, but it was found that StatModels does not support firm (entity) and year fixed effects. This limitation means that to use StatModels, dummy variables for firms and years need to be created. While using dummy variables for years as year fixed effects does not significantly increase the runtime, using dummy variables for firms adds at least 20 minutes to the runtime. This additional time is not optimal for efficient analysis, leading to the decision to avoid using StatModels in this context Seabold and Perktold, 2010.

PanelOLS, on the other hand, simplifies the process by including entity and time fixed effects directly. This inclusion makes the modelling process more straightforward and efficient. Additionally, there is no need to include industry-level year fixed effects in the model when running in Python. This is because PanelOLS already accounts for entity and time fixed effects, reducing the computational burden. By using PanelOLS, the analysis becomes more efficient and less time-consuming. This approach ensures that the models are both accurate and practical for the study Sheppard et al., 2024.

4 Results and Discussions

This section presents the findings from the analysis of the "Ricochet-recovery" loan's impact on credit spreads for SMEs. Utilising various analytical models, including two-way fixed effects and long-term effects analysis, the study examines the period before and after the policy implementation (2017-2019 and 2020-2022). The objective is to identify shifts in lenders' risk perception and the differential impact on eligible versus non-eligible firms. The section includes an initial data description, results of the models, and a discussion of the findings.

The initial data section presents visualisations that facilitate the data filtering process, as detailed in chapter 3. The original dataset comprised 12,013 firms, with 5,697 categorised as non-eligible and 6,316 as eligible entities, spanning 78 distinct sectors. These visualisations illustrate the distribution and characteristics of the dataset, aiding in the identification of patterns and outliers that inform the data filtering process. The results section summaries the findings from the models and provides evidence of the policy's impact. This is followed by a discussion that compares these findings with those from other studies and addresses the limitations of the current analysis.

4.1 Initial Data

This section provides initial sets of data visualisations that aid in filtering the data, as explained in chapter 3. Before proceeding with the results of the study, the initial dataset comprised a total of 12,013 firms. These firms were categorised into 5,697 non-eligible and 6,316 eligible entities, as shown in figure 4.1, spanning 78 distinct sectors. The visualisations in this section illustrate the distribution and characteristics of the dataset. By examining these visualisations, patterns and outliers can be identified, informing the data filtering process. This comprehensive dataset serves as a robust foundation for the analysis.

As illustrated in figure 4.2, numerous sectors contain fewer than 250 SMEs. In stark contrast, the top five sectors each boast over 500 SMEs. Additionally, the proportion of eligible versus non-eligible SMEs varies markedly across sectors. For example, within the top ten sectors, several commence with a NACE code[1] starting with 4, while others begin with 5, 6, or 8. Some sectors are composed exclusively of either eligible or non-eligible firms. Notably, five sectors each encompass only a single SME: sector 84 (Public administration and defence; compulsory social security), sector 51 (Transport), sector 39 (Remediation activities and other waste management services), sector 97 (Activities of households as employers of domestic personnel), and sector 99 (Activities of extraterritorial organisations and bodies).

[1]The NACE code description is available in the appendix A.1.

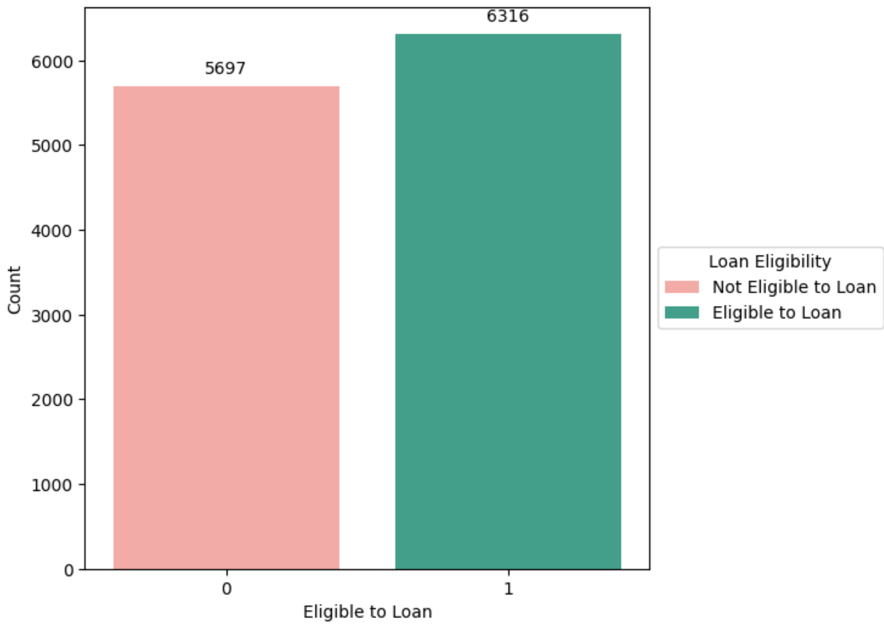

Figure 4.1: Number of SMEs based on the eligibility criteria.

The dataset of SMEs shows a notable similarity to the overall population of SMEs, with the top ten sectors including retail trade, specialised construction activities, wholesale trade, food and beverage services, and more, as shown in figure 4.3. When compared to the pie chart from the chapter 2, retail trade aligns with the wholesale and retail trade category, specialised construction activities and construction of buildings fall under construction, and food and beverage services match accommodation and food service activities. This comparison serves to illustrate the diversity and distribution of SMEs across a range of sectors, thereby demonstrating the representativeness of the dataset with respect to the broader SME population.

Upon further examination of the data illustrated by the figure 4.4, it is evident that non-eligible SMEs consistently exhibit higher average financial debts compared to their eligible counterparts throughout the period from 2017 to 2022. This disparity is significant, with the average financial debts of non-eligible SMEs being nearly twice that of eligible SMEs. For instance, in 2017, the average financial debt (in thousands of euros) for non-eligible SMEs was approximately 437.13, while for eligible SMEs, it was around 275.00.

Interestingly, non-eligible and eligible companies have the highest levels of debt, reaching 454.25 in 2019 and 306.24 in 2020, respectively. This spike in debt can be attributed to the economic impact of the Covid-19 pandemic, which led to increased borrowing to support operations during periods of falling revenues and economic uncertainty. The lockdowns and restrictions induced by the pandemic probably forced many SMEs to rely more heavily on external financing to cover operational costs, maintain cash flow, and navigate a difficult economic environment. Higher debt levels in 2019 for non-eligible SMEs may also reflect their limited access to financial resources, making them more vulnerable to economic shocks and forcing them to borrow more to stay afloat. Despite these higher debts, the financial stability of non-eligible companies appears relatively unchanged over time, indicating a consistent ability to manage their debt levels without significant fluctuations.

In contrast, eligible SMEs demonstrate a higher average investment ratio than non-eligible SMEs. Although the trends in financial debts are more straightforward, both types of SMEs display a similar pattern in investment behaviour, as illustrated in figure 4.5. Specifically, there is a noticeable decline in investment between 2019 and 2020, reaching its lowest point in 2020. While the eligible firms still have an average investment ratio above 2%, the non-eligible SMEs

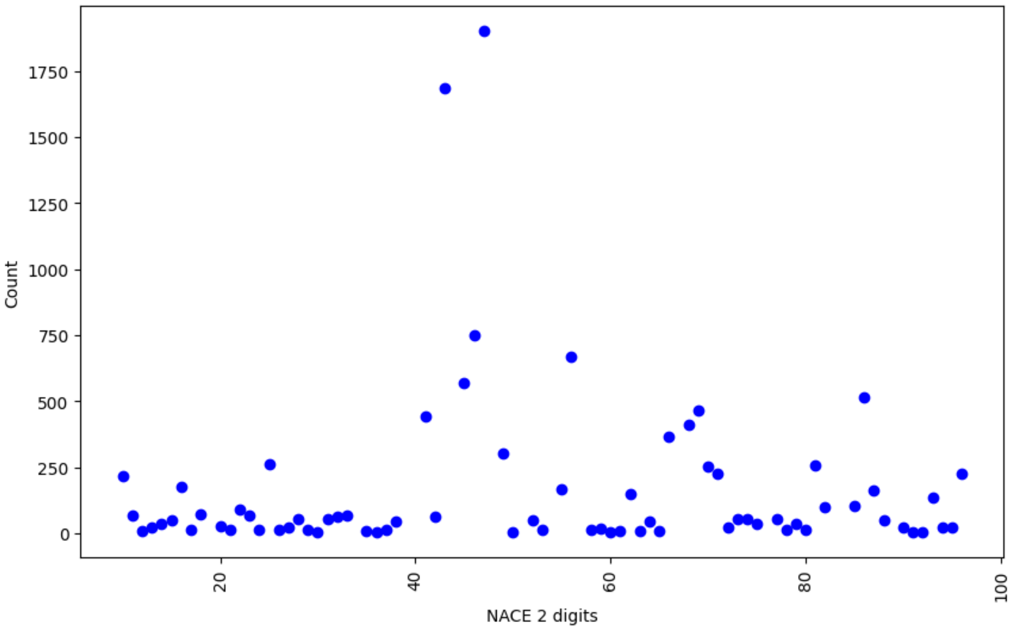

Figure 4.2: Distribution of SMEs across different sectors.

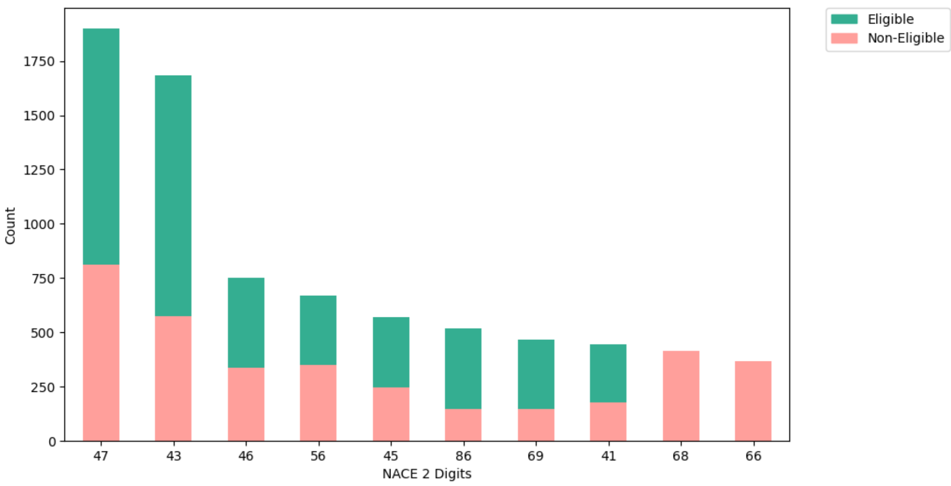

Figure 4.3: Top ten sectors as determined by NACE code digits.

have a rate nearly at -4%. Given that investment is defined as the rate of investment in tangible assets, it implies that eligible companies continued to invest in assets during the pandemic; whereas non-eligible companies sold their assets, resulting in a lower amount of tangible assets in 2020 compared to 2019. Despite this drop, investment levels increased in 2021, indicating a recovery phase for both types of firms: eligible SMEs saw an increase from a 2.26% investment rate in 2020 to 3.26%, and non-eligible SMEs improved from -3.67% in 2020 to 0.07%.

Since the eligibility criteria are based on financial stability, the observations show that eligible SMEs are faring better than their non-eligible counterparts. Eligible SMEs exhibit higher investment levels and lower financial debts, indicating a stronger financial position. This suggests they have better access to internal resources, allowing them to finance operations and growth without relying heavily on external debt. Their financial stability likely provides them with more advantageous terms when accessing external financing, resulting in lower borrowing costs. The ability to maintain lower financial debts while achieving higher investment levels highlights their financial resilience.

Conversely, non-eligible SMEs, with their higher financial debts and lower investment ratios,

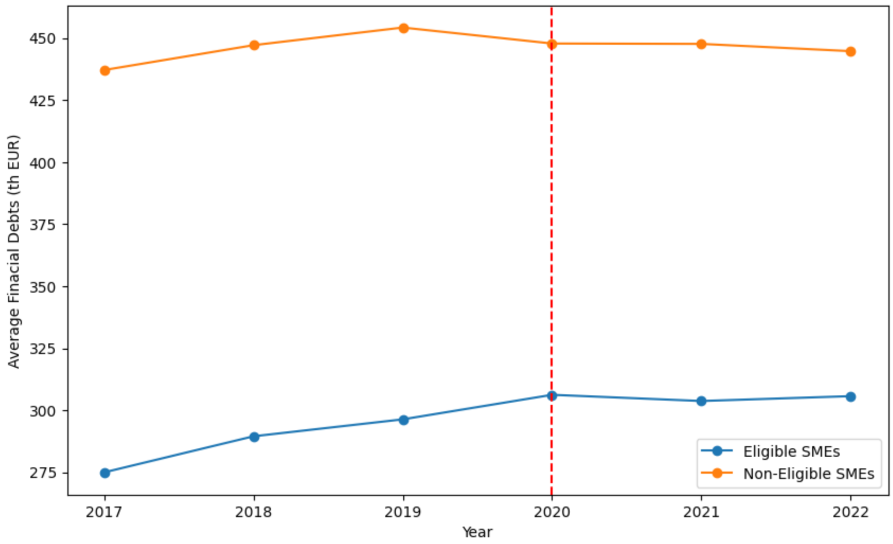

Figure 4.4: Average financial debts before and after the policy.

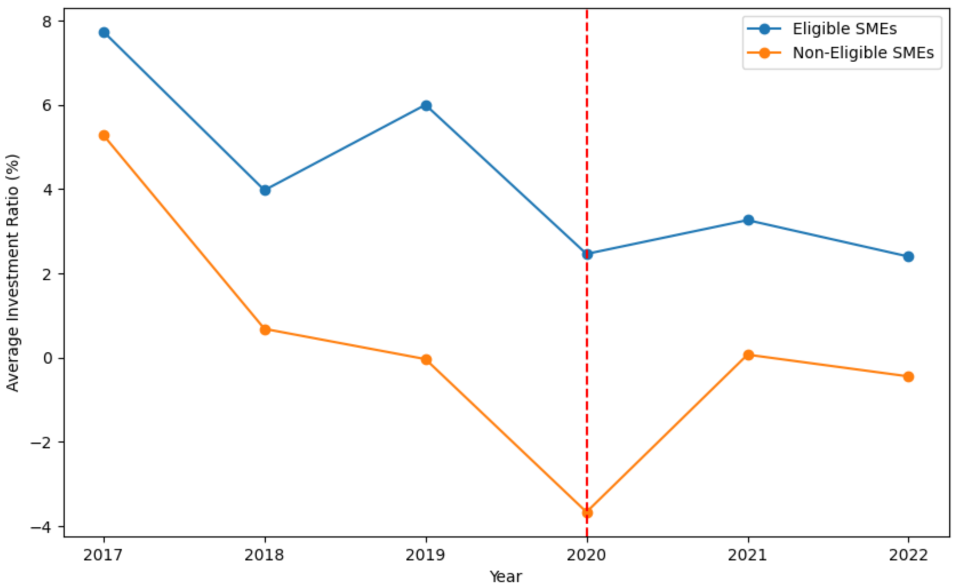

Figure 4.5: Average investment ratio before and after the policy.

appear to depend more on external financing sources. This reliance on external debt may be due to limited internal resources and higher operational costs, which can hinder their ability to invest in growth opportunities. The higher financial debts of non-eligible SMEs also suggest that they face greater financial challenges, potentially impacting their long-term sustainability and competitiveness. The distinction in financial behaviour between eligible and non-eligible SMEs highlights the advantages of financial stability in terms of investment capacity and access to favourable financing options.

These observations confirm that the perceived risks are lower for eligible SMEs. This lower risk perception suggests improved access to external lending and lower borrowing costs. The data indicates they are in a stronger financial position, enhancing their attractiveness to lenders. Consequently, this could lead to more advantageous borrowing terms and conditions. These findings provide a preliminary indication of improved access to external financing and support the results outlined in the next section.

4.2 Results

The dataset used in the various models is illustrated in figure 4.6 and it comprises 9,263 SMEs, with 5,484 eligible companies and 3,779 non-eligible companies. Given the application of DiD models, it is essential to ensure the presence of at least two companies with both types of eligibility. As a result, 19 sectors containing only one type of SME were excluded. Consequently, the number of ineligible companies has decreased more significantly than the number of eligible companies compared to the initial dataset in figure 4.1, due to the exclusion of sectors containing only ineligible companies. The remaining dataset henceforth comprises 59 sectors, as detailed in appendix appendix A.2.

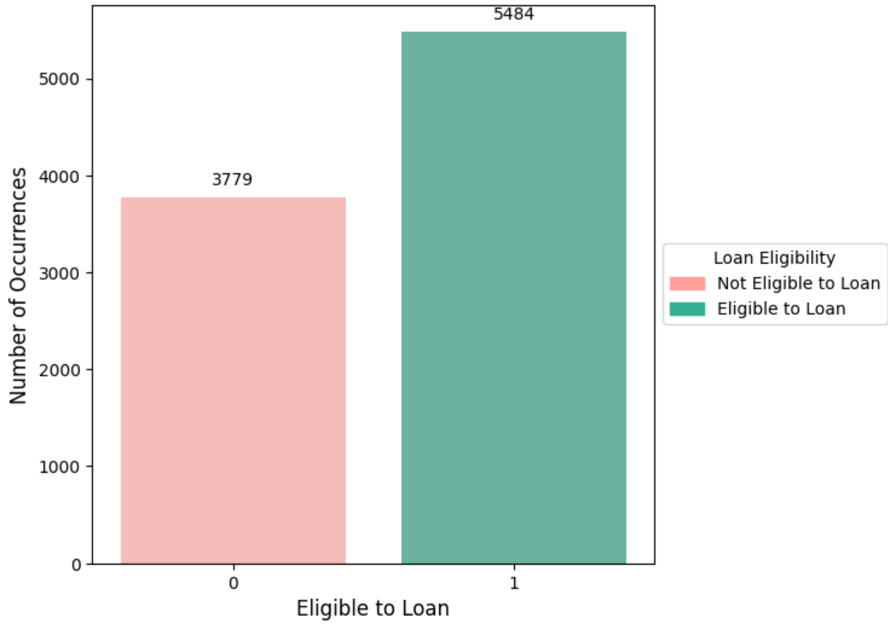

Figure 4.6: Number of SMEs categorised by loan eligibility post filtering process.

Each analysis except the placebo test involves two different models: one without control (Xa, X being the order of the model study. ex: Two-ways fixed effect is the first model studied, thus X is 1) variables and one with control variables (Xb). The model without control variables helps to understand the direct relationship between the independent and dependent variables, providing a baseline for comparison. This version shows the raw effect without any adjustments and tests the robustness of the relationship in its simplest form. In contrast, the model with control variables isolates the effect of the independent variable by accounting for other factors that might influence the outcome. This approach improves model accuracy by reducing bias and providing a more precise estimate of the relationship. Additionally, it assesses the impact of control variables by showing how much additional variation is explained and tests the robustness of the relationship under more realistic conditions.

To assess whether the "Ricochet-recovery" loan has an impact on the spread, the two-way fixed effects model is first studied. The results in table 4.1 show that the coefficient β^k of the treatment ($\text{After}_t \times \text{E}_t$) variable in both Model 1a and Model 1b is statistically significant at the 1% level. The treatment effect is smaller in Model 1b compared to Model 1a, indicating that some of the effect observed in Model 1a is explained by the control variables. The inclusion of control variables in Model 1b helps to isolate the treatment effect by accounting for other factors that influence the spread. The statistically significant control variables (Debt to Asset Ratio Lagged, and Cash to Asset Ratio Lagged) suggest that these factors have a meaningful impact on the spread.

Table 4.1: Impact of treatment on credit spread.

	Model 1a	**Model 1b**
Treatment	-0.603†	-0.487‡
	(0.224)	(0.227)
CV: Equity to Asset Ratio Lagged		0.008
		(0.013)
CV: Debt to Asset Ratio Lagged		-0.140†
		(0.035)
CV: Cash to Asset Ratio Lagged		-0.048†
		(0.017)
CV: Operational Profit to Asset Ratio Lagged		-0.001
		(0.011)
FE: Entity	X	X
FE: Year	X	X
Num. Obs.	55578	55578

† $p < 0.01$
‡ $p < 0.05$

The analysis reveals that the government-backed "Ricochet-recovery" loan has, on average, lowered the credit spread of eligible firms by 0.487 basis points. This statistically significant reduction in credit spread indicates that the loan has effectively reduced borrowing costs for these firms. It can be therefore affirmed that the hypothesis of which the loan has no impact on the credit spread can be rejected at the 99% confidence level, as the treatment effect in both models (1a and 1b) is statistically significant at the 1% level. This means that the probability of observing such a treatment effect by random chance is less than 1%, providing strong evidence that the "Ricochet-recovery" loan does indeed have an impact on the credit spread.

The evidence suggesting a positive relationship between the eligible firms and the "Ricochet-recovery" loan may be subject to a false negative, implying that this relationship might have been observed even before the enactment of the treatment. The two-way fixed effects model does not provide conclusive evidence to refute this possibility. To examine whether the policy had no effect prior to its enactment and support the parallel trends assumption, a long-term effects analysis is conducted. The results of this analysis are summarised in figure 4.7.

It is evident that the beta coefficients for both models are close to zero before the policy implementation (2017-2019). This observation indicates that there were no significant differences in the credit spreads between the treatment and control groups prior to the loan implementation. Such a finding supports the parallel trends assumption, which is crucial for the validity of the DiD model. By demonstrating that the credit spreads were similar before the policy, it can be inferred that any observed changes post-implementation are likely due to the policy itself. This strengthens the argument that the "Ricochet-recovery" loan had a genuine impact on the credit spreads. Overall, the close-to-zero beta coefficients provide strong evidence that the parallel trends assumption holds true in this context.

Furthermore, the long-term effects model reveals that following the policy implementation (2020-2022), the beta coefficients for both models are mostly below zero. This indicates a reduction in the credit spread for eligible firms compared to non-eligible firms following the policy change. The beta coefficients in Model 2b (with control variables) are generally smaller in magnitude compared to Model 2a (without control variables). This suggests that some of the observed effect in Model 2a is explained by the control variables included in Model 2b. The error bars on each data point show some variability, but the overall trend suggests a negative impact on the credit spread, implying that the "Ricochet-recovery" loan effectively lowered borrowing costs for eligible firms.

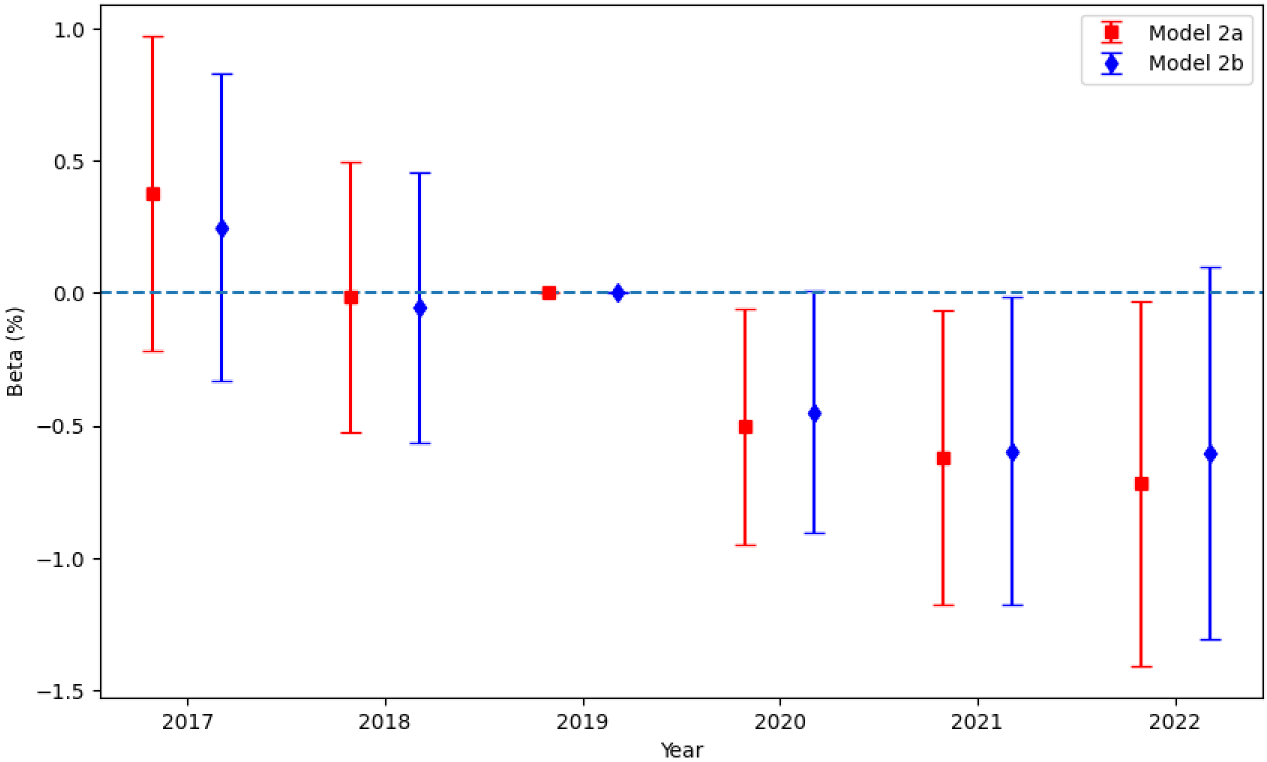

Figure 4.7: Long-term effects on credit spread gap: beta differences between eligible and non-eligible firms (2017-2022).

To further verify the plausibility of the parallel trends assumption, a robust placebo test with fake treatment periods was used. In the first test, 2017 was used as the fake treatment period, so Before_t represents 2017. In the second test, 2018 was used as the fake treatment period, so Before_t includes both 2017 and 2018. The results for the second-period treatment (using 2017 as the fake treatment period) show a treatment effect of -0.140 with a standard error of 0.276. For the third-period treatment (using 2018 as the fake treatment period), the treatment effect is -0.108 with a standard error of 0.252. Both models include fixed effects for entities and years, with standard errors clustered at the eligible level. The treatment effects for both periods are not statistically significant, indicating no significant pre-existing trends that could bias the results. This supports the validity of the original DiD model, suggesting the observed treatment effect is not due to pre-existing differences between the treatment and control groups.

Table 4.2: Placebo DiD estimates using fake treatment periods.

	Second-Period Treatment	**Third-Period Treatment**
Treatment	-0.140	-0.108
	(0.276)	(0.252)
Num. Obs.	27,789	27,789
FE: Entity	X	X
FE: Year	X	X

Evidence shows that the "Ricochet-recovery" loan significantly impacts lenders' risk perception, raising the question of whether the debt levels of treated firms after policy implementation affect credit spreads differently compared to other SMEs. To explore this, the analysis examines the sensitivity of credit spreads to firms' debt levels and determines if this sensitivity varies by eligibility. By dividing the period into two sub-periods (2017-2019 and 2020-2022), any shifts in the relationship between credit spreads and firms' indebtedness can be identified. The model studied can be referred to in the second model section of chapter 3.

While the initial analysis confirms that the "Ricochet-recovery" loan significantly reduces credit spreads, it does not fully explain how this effect varies with different levels of firm indebtedness. By examining the sensitivity of credit spreads to debt levels, it is possible to determine how the policy has altered the relationship between debt levels and borrowing costs for eligible firms. This analysis provides a more nuanced view of the policy's effectiveness by highlighting the differential impact on eligible versus non-eligible firms. A greater reduction in sensitivity for eligible firms compared to non-eligible firms suggests that the policy has been particularly beneficial for those it was designed to support. Additionally, comparing the two sub-periods can reveal any shifts in lenders' risk perception. If the policy has successfully mitigated the perceived risks associated with higher debt levels, this should be reflected in a reduced sensitivity of credit spreads to debt levels in the post-implementation period.

Table 4.3: Sensitivity of credit spreads to debt levels.

	Model 1a	**Model 1b**
Debt Ratio	-0.059†	-0.101†
	(0.018)	(0.034)
Debt Ratio x Eligible	-0.136†	-0.122†
	(0.019)	(0.027)
Debt Ratio x After	0.008	-0.008
	(0.018)	(0.013)
Debt Ratio x Eligible x After	-0.041†	-0.028†
	(0.006)	(0.006)
CV: Equity to Asset Ratio Lagged		-0.014
		(0.009)
CV: Cash to Asset Ratio Lagged		-0.040†
		(0.014)
CV: Operational Profit to Asset Ratio Lagged		-0.003
		(0.009)
FE: Entity	X	X
FE: Year	X	X
Num. Obs.	55578	55578

† $p < 0.01$

The results summarised in table 4.3 provide evidence that the "Ricochet-recovery" loan significantly impacts lenders' risk perception, especially for eligible firms. The negative coefficients for the Debt Ratio in both models indicate that higher debt levels are associated with lower credit spreads for non-eligible firms. The effect is even more pronounced for eligible firms before the policy implementation, as shown by the significant negative coefficients for the Debt Ratio × Eligible interaction term. Specifically, an increase of 1 percentage point in the debt ratio is associated with a decrease of 0.101 basis points in credit spread for non-eligible firms and a decrease of 0.122 basis points for eligible firms, which is 0.021 basis points more. This implies that the perceived risks for eligible firms, which are financially stable SMEs, are lower compared to non-eligible firms, leading to more advantageous borrowing costs.

The results further reveal that the "Ricochet-recovery" loan has mitigated the perceived risks associated with higher debt levels for eligible firms after the policy implementation, even during the uncertainty surrounding Covid-19. The significant negative coefficients for the Debt Ratio × Eligible × After interaction term in both models indicate that the relationship between debt levels and credit spreads remains advantageous for eligible firms post-implementation. This decrease is less pronounced in the post-implementation period, indicating a smaller reduction in basis points compared to the pre-implementation period.

Additionally, the Debt Ratio × After variable, which represents the debt ratio after the implementation for non-eligible SMEs, has a really small (i.e., -0.008) coefficient, indicating that an increase of 1 unit in debt ratio leads to a really small decreased of credit spread. It shows no significant impact to the credit spreads as their p-value is not significant at 0.1, suggesting that the policy's effect is specific to eligible firms. This finding aligns with the fact that policy helps eligible firms during the pandemic and improve their access to financing during period of uncertainty.

By comparing the two sub-periods (2017-2019 and 2020-2022), the analysis identifies shifts in lenders' risk perception, further highlighting the policy's effectiveness. The reduced sensitivity of credit spreads to debt levels in the post-implementation period for eligible firms suggests that the "Ricochet-recovery" loan has been particularly beneficial for those it was designed to support. This differential impact on eligible and non-eligible firms provides a nuanced view of the policy's success in achieving its goals. Overall, the results underscore the importance of targeted financial interventions in supporting SMEs during challenging economic times, such as the pandemic, and demonstrate the positive outcomes of the "Ricochet-recovery" loan in fostering a more favourable lending environment for eligible firms.

When comparing these results with Kim's study, similar findings emerge. Kim's analysis supports the evidence that the sensitivity of credit spread to the debt ratio decreased for eligible firms post-policy, while there was no change for non-eligible firms. This suggests that the policy did not significantly impact non-eligible firms but did for eligible firms. In terms of basis points, both results show similar trends, indicating consistency and reliability. The decrease in credit spread for eligible firms and the reduced sensitivity in Kim's study both highlight the significant impact of the policy on eligible firms.

4.3 Discussions

The analysis demonstrates that the "Ricochet-recovery" loan significantly reduces credit spreads for eligible firms, underscoring the policy's effectiveness. The two-way fixed effects model and long-term effects analysis confirm that the observed changes are likely attributable to the policy itself. The placebo test further supports the robustness of these findings. Evidence indicates that the loan impacts lenders' risk perception, with a greater reduction in sensitivity to debt levels for eligible firms compared to non-eligible firms, particularly when examining the two sub-periods (2017-2019 and 2020-2022).

Overall, the results highlight the importance of targeted financial interventions in supporting SMEs during challenging economic times. Notably, several studies have utilised credit spreads as a proxy for perceived risk and borrowing costs, which aligns closely with the findings of this analysis. Comparing these results with Kim's study reveals similar findings, showing that the policy significantly impacts eligible firms by reducing credit spreads and sensitivity to debt ratios. Both studies highlight the policy's success in fostering a more favourable lending environment for eligible firms. Further, findings by Akinci and Queralto, 2022 emphasise the importance of policy measures in stabilising credit markets, which is consistent with the observed reduction in credit spreads for eligible firms under the "Ricochet-recovery" loan. Additionally, Caldara and Herbst, 2016 explored the interaction between monetary policy, financial markets, and the real economy, discovering that monetary policy shocks significantly influence fluctuations in industrial output and corporate credit spreads. This study supports the notion that financial interventions can have a substantial impact on credit spreads, similar to the effects observed with the "Ricochet-recovery" loan.

However, there are several limitations of the models used in this analysis. Firstly, the models include only four financial control variables, which may not fully capture the complexity of factors influencing credit spreads, potentially leading to omitted variable bias. Additionally, the inclusion of more comprehensive fixed effects could improve the robustness of the models by accounting for broader market influences. Heterogeneity among firms is another limitation, as the analysis assumes a uniform impact of the "Ricochet-recovery" loan across all eligible firms.

Therefore, future research could benefit from incorporating a more extensive set of control variables as well as considering heterogeneity among firms could further enhance the robustness of the findings. By examining the differential impact of the "Ricochet-recovery" loan across various firm characteristics, such as size, industry, and financial health, could provide deeper insights into the policy's effectiveness.

Incorporating qualitative research methods, such as interviews and case studies, could complement the quantitative analysis by providing a deeper understanding of the experiences and perspectives of SMEs and lenders regarding the "Ricochet-recovery" loan. Qualitative insights can reveal the practical challenges and benefits of the policy, offering a more holistic view of its impact. For example, interviews with SME owners could uncover how the loan has influenced their business operations and financial stability, while case studies could highlight specific success stories or areas for improvement.

By addressing these areas, future research can build on the current findings and contribute to a more comprehensive understanding of the impact of targeted financial interventions on SMEs.

5 Conclusion

This study provides a comprehensive analysis of the impact of a loan policy implemented during the pandemic on borrowing costs for Belgian SMEs. The initial phase of the analysis involved the development of various models to examine borrowing costs, with a particular focus on the influence of loan eligibility on the credit spread. The results indicate a significant treatment effect, demonstrating that loan eligibility substantially reduces the credit spread, thereby lowering borrowing costs. To validate the parallel trends assumption, an examination of the long-term effects was conducted, revealing that the policy's pre-treatment implementation had minimal to no effect. Furthermore, a placebo test using two fake treatment periods confirmed that the observed effects were not false positives.

Subsequent analysis focused on the sensitivity of credit spreads to debt ratios. The findings indicate that eligible firms with high debt ratios experienced lower credit spreads compared to non-eligible firms, suggesting that financially stable firms benefit from reduced borrowing costs. Post-treatment analysis revealed that the debt ratio of non-eligible firms did not significantly affect the credit spread, whereas the debt ratios of eligible firms continued to have a significant impact even during the pandemic. These results underscore the effectiveness of the loan policy in lowering borrowing costs and enhancing access to financing for the intended firms.

In conclusion, this study provides robust empirical evidence that loan eligibility significantly reduces the credit spread, thereby lowering borrowing costs. The findings further confirm that loan policies are effective in reducing borrowing costs and improving access to financing for eligible firms, even during a pandemic. These results have important implications for government policy, offering a solid foundation for designing future loan policies aimed at supporting financially stable firms and enhancing access to financing. The study's findings highlight the critical importance of targeted loan policies in promoting financial stability and economic resilience.

A
Annex

A.1 NACE 2 Digits

The "NACE 2 Digits" are the 2 first digits of the code NACE 2008. These categorisation and descrition come from Bel-first van Dijk, 2024.

NACE 2 digits code	Description
01	Crop and animal production, hunting and related service activities
02	Forestry and logging
03	Fishing and aquaculture
05	Mining of coal and lignite
06	Extraction of crude petroleum and natural gas
07	Mining of metal ores
08	Other mining and quarrying
09	Mining support service activities
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products

27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply
36	Water collection, treatment and supply
37	Sewerage
38	Waste collection, treatment and disposal activities; materials recovery
39	Remediation activities and other waste management services
41	Construction of buildings
42	Civil engineering
43	Specialised construction activities
45	Wholesale and retail trade and repair of motor vehicles and motorcycles
46	Wholesale, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines
50	Water transport
51	Air transport
52	Warehousing and support activities for transportation
53	Postal and courier activities
55	Accommodation
56	Food and beverage service activities
58	Publishing activities
59	Motion picture, video and television programme production, sound recording and music publishing activities
60	Programming and broadcasting activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
64	Financial service activities, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security
66	Activities auxiliary to financial services and insurance activities
68	Real estate activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
71	Architectural and engineering activities; technical testing and analysis

72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
77	Rental and leasing activities
78	Employment activities
79	Travel agency, tour operator and other reservation service and related activities
80	Security and investigation activities
81	Services to buildings and landscape activities
82	Office administrative, office support and other business support activities
84	Public administration and defence; compulsory social security
85	Education
86	Human health activities
87	Residential care activities
88	Social work activities without accommodation
90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities
92	Gambling and betting activities
93	Sports activities and amusement and recreation activities
94	Activities of membership organisations
95	Repair of computers and personal and household goods
96	Other personal service activities
97	Activities of households as employers of domestic personnel
98	Undifferentiated goods- and services-producing activities of private households for own use
99	Activities of extraterritorial organisations and bodies

A.2 Distribution of SMEs Across Different Sectors

The table bellow shows the distribution of eligible and non-eligible SMEs across different sectors. These distributions consist of the final dataset after the filtering process. Furthermore, the relevant sectors are defined in the above section (see appendix A.1).

Eligible_to_Loan	0	1	total
NACE_2_digits			
47	692	923	1615
43	510	974	1484
46	277	336	613
56	294	275	569
45	205	273	478
86	128	344	472
69	126	289	415
41	147	229	376
81	82	150	232

25	109	118	227
70	86	140	226
96	96	103	199
10	102	96	198
71	74	121	195
16	62	101	163
55	78	77	155
87	52	83	135
93	70	53	123
62	50	69	119
82	41	48	89
22	35	51	86
11	28	36	64
23	27	32	59
18	27	32	59
32	19	39	58
33	24	32	56
42	21	33	54
31	21	29	50
77	20	28	48
15	18	30	48
74	17	29	46
52	22	23	45
73	21	24	45
88	16	29	45
28	18	25	43
38	20	20	40
75	9	23	32
14	9	23	32
79	10	16	26
94	6	14	20
20	6	14	20
72	10	9	19
13	9	10	19
27	12	7	19
95	5	13	18
29	4	10	14
80	9	3	12
21	6	6	12
26	6	5	11
61	4	7	11
37	4	6	10
53	6	4	10
24	5	4	9
78	6	3	9
17	7	2	9
58	2	6	8
63	4	3	7

60	3	1	4
50	2	1	3
Sum	3779	5484	9263

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Executive Summary[1]

Small and Medium-sized Enterprises (SMEs) are crucial to the Belgian economy, representing 99.9% of all enterprises and employing over 1.1 million individuals. Despite their importance, SMEs often struggle with financing, a challenge worsened by the Covid-19 pandemic. In response to these challenges, the Belgian Government has launched various policy initiatives at both federal and regional levels. One such measure, implemented in the Walloon region, is the "Ricochet-recovery" loan, distinguished by its 0% interest rate, making it an appealing option for businesses seeking financial support.

This study investigates the impact of the "Ricochet-recovery" loan on the credit spreads and financial health of Belgian SMEs. By utilising a dataset of 9,263 SMEs from 2017 to 2022, the research employs a Difference-in-Differences (DiD) approach to compare financial outcomes between eligible and non-eligible firms. The findings indicate that the loan policy significantly reduced credit spreads for eligible SMEs, suggesting improved creditworthiness and lower borrowing costs. Additionally, the study highlights enhanced financial access for eligible firms, both before and after the policy enactment.

These results demonstrate the effectiveness of targeted financial interventions in supporting SMEs during economic downturns. Policymakers can use these insights to design future policies that ensure SMEs receive necessary support, maintaining financial stability and fostering a resilient economic environment.

[1]Word Count : 15,869