Lower bank capital requirements as a policy tool to support credit to SMEs: evidence from a policy experiment*

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Abstract : Starting in 2014 with the implementation of the European Commission Capital Requirement Directive, banks operating in the Euro area were benefiting from a 25% reduction (the Supporting Factor or "SF" hereafter) in own funds requirements against Small and Medium-sized enterprises ("SMEs" hereafter) loans. We investigate empirically whether this reduction has supported SME financing and to which extent it is consistent with SME credit risk. Economic capital computations based on multifactor models do confirm that capital requirements should be lower for SMEs. Taking into account the uncertainty surrounding their estimates and adopting a conservative approach, the SF is consistent with the difference in economic capital between SMEs and large corporates. As for the impact on credit distribution, our differences-in-differences specification enables us to find a positive and significant impact of the SF, particularly on the largest and the safest SMEs, as well as on the smallest eligible exposures. While the SF improves the credit supply to the least constrained firms, it also targets its impact on the healthiest borrowers, which is highly desirable from a regulatory perspective.

Keywords : SME finance, Credit supply, Basel III, Credit risk modelling, SME Supporting Factor

JEL-Classification : C13, G21, G33

*The opinions expressed in the paper represent the authors personal opinions and do not necessarily reflect the views of the ACPR - Banque de France or their staff.

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1 Introduction

Small and Medium-sized Enterprises ("SMEs" hereafter) finance is a growing concern in Europe. While SMEs are a crucial engine for growth in Europe, they are largely dependent on bank credit regarding their external financing and are much more likely to report issues with bank financing than large corporates. As an illustration, in 2014, bank lending to SMEs was still below its pre-crisis level, in contrast with large corporates (EBA, 2016). To improve SMEs' access to credit in time of crisis, policymakers and central bankers traditionnally rely on monetary and targeted fiscal policies.[1] However, in a context of changing bank regulation and rising bank capital requirements ("CRs" hereafter), bank lending decision has also become increasingly more sensitive to the regulatory framework, as illustrated by recent contributions to the empirical literature.[2] Against this background, this paper investigates the *effectiveness* and the *consistency* of a new regulatory tool implemented specifically to promote SMEs' access to bank credit: a targeted reduction in bank CRs associated with SMEs loans.

In 2014, the transposition of the Basel III standards into EU law introduced a 24% reduction in CRs for exposures to SMEs –labelled *Supporting Factor* ("SF" hereafter)– with the aim of fostering the provision of credit to SMEs. The idea behind this proposal is that any reduction of regulatory capital requirements (CRs) should boost credit availability for businesses. The European legislators has required credit institutions to use this CRs relief for the "*exclusive purpose of providing an adequate flow of credit to SMEs established in the Union*".[3] But, a necessary condition for the Supporting Factor to be effective is that regulatory capital requirements should be consistent with the underlying SME credit risk. Hence, as required by the legislators themselves, this targeted reduction in CRs needs to be regularly evaluated according to two criteria: (i) an easier access to bank credit for SMEs and (ii) the consistency of capital requirements with SME credit risk.

In this paper, we assess this policy experiment along with these two dimensions. For this purpose, we exploit the French credit register. This dataset is maintained by the Banque de France and offers an almost comprehensive sample of loans granted to corporate businesses operating in France over the last two decades. Importantly, in this dataset, we also observe the credit rating granted by the Banque de France to a large sub-sample of firms, which enables the computation of historical time series of default rates. Using this dataset, the consistency of the reform regarding the intrinsic riskiness of SMEs is gauged through the computation of banks' *economic* capital requirements using the structural credit

[1] During the financial crisis, targeted monetary policy instruments such as the TLTRO or the ACC have been implemented in Europe. In France, SMEs benefit from specific fiscal deductions related to their investment plan.

[2] See for instance Behn et al. (2016), Bonner and Eijffinger (2016), Jimenez et al. (2017), or Fraisse, Lé, and Thesmar (*forthcoming*) respectively in the case of Germany, the Netherlands, Spain and France.

[3] See paragraph 44 of the Capital Requirement Directive (CRDIV) published in the Official Journal of the European Union the 27 June 2013.

risk framework underlying the computation of the regulatory capital requirements. Then, the impact of the reform on the credit supply to targeted SMEs is estimated through the differences-in-differences methodology.

To assess the reform regarding its consistency with the riskiness of SMEs lending (we refer to this part as the *risk analysis* hereafter), we build upon the credit risk structural approach (Merton, 1974), which is the approach underlying the Basel II/III regulatory CRs formula (Gordy, 2003). This method allows us to compute the marginal contribution of specific groups of firms to the total credit risk of the portfolio. This marginal contribution measures the amount of *economic* capital required to cover potential losses on bank loans.[4] In this paper, we perform the computation of economic capital at the level of sub-portfolios depending on the firm size, the latter being assumed to reflect common risk characteristics.

In particular, we expand the Asymptotic Single Risk Factor (ASRF) model to a multi-factor framework, by assuming that systematic risk factors are linked to size classes. That allows us to compute the contribution of each size class to the total risk of the portfolio, taking into account the potential *diversification* or *concentration* effects within the portfolio. Indeed, in the Basel II/III regulatory formulas, assets correlations are assumed (i) to depend only on the probability of default ("PD" hereafter) and (ii) to be invariant with the real composition of each bank's portfolios. As a result, SMEs credit risk can be overestimated by the current regulation[5] if the regulatory assets correlation is significantly higher than the empirical assets correlation estimated using data of banks' portfolios.[6] Thus, the challenge is to assess whether SMEs are really more sensitive to systematic risk factor and more correlated between them. The measurement of assets correlation in real banks' portfolios is the only way to answer this question. Hence, to gauge the possible over(under)-estimation of SMEs credit risk in the current regulation as well as the appropriateness of the SF, we finally compare the "economic" CRs resulting from our multifactor model with the regulatory ones, with and without considering the reduction associated to the SF.

For being eligible to the Supporting Factor, SMEs must have (i) an annual turnover lower than €50 million and (ii) a total outstanding amount of credit with a given banking group lower than €1.5 million. We take advantage of this setting to estimate the effect of the SF on the provision of credit to targeted SMEs (we refer to this part as the *credit analysis* hereafter) using a differences-in-differences approach. We first restrain the sample to SMEs, identified as the firms with a turnover lower than €50million. Then, we define a treatment group made of eligible exposures from pairs of bank-firm with a total outstanding amount below €1.5 million and a control group made of (ineligible) exposures from the remaining

[4]Economic capital can be defined as the estimate of the worst possible decline in the bank's amount of capital at a specified level of confidence (99.9% in Basel formulas) within a chosen time horizon (one year).

[5]These firms display a higher probability of default than large companies, which implies higher capital requirements, even if regulatory formulas assume a negative relationship between the probability of default and the assets correlation

[6]See Dietsch et al. (2016) for a comprehensive overview of the existing empirical studies on the relationship between asset correlations and firm size.

pairs of bank-firm. We then compare the evolution of the outstanding amount of credit of eligible and ineligible exposures after the reform (vs. before the reform). We deal carefully with possible identification issues by running several robustness checks.

After having estimated the average effect of the SF on the credit supply to eligible firms, we then investigate the dynamics of this effect over time. Did the banks respond immediatly to the reform or, on the contrary, has the SF become increasingly effective quarter after quarter ? To that end, we estimate the effect of the SF *within* each quarter, both before and after the reform. In doing so, we not only gather information about the evolution of the effectiveness of SF over time but we also test a fundamental assumption of the differences-in-differences estimator: the parallel trend assumption. In a third time, we investigate possible sources of heterogeneity in the effect of the SF. We focus on two crucial firm characteristics : the size and the riskiness of firms. We classified exposures according to the turnover and the Banque de France rating of firms in the pre-reform period (to avoid any endogeneous feedback loops) and we test whether the effect of the SF is the same for the various groups of firms.

Finally, we explore possible non-linearities by estimating the effect of the SF *conditional* on the ex ante size of the exposures. For this purpose, we classify exposures into three buckets based on their average outstanding amount computed over the pre-reform period and we estimate an effect of the SF separetely for each of these buckets. As it will become clear in the next paragraphs, there are some reasons to think that all exposures have not benefited in the same way from the SF, owing to the design of the SF.

Our main results can be summarized as follows. Regarding the *risk analysis*, the computation of economic CRs based on a multifactor framework and its comparison with Basel III regulatory CRs do confirm that the CRs should be lower for SMEs than for large corporates. We first find that the largest firms are the most exposed to systematic risk, *i.e.* they are the most exposed to general economic conditions even if their default rates are low. Second, the results of the estimation confirms the potential for diversification provided by the presence of exposures on SMEs in the total bank loans portfolio : while the classes of medium-sized and large firms are highly correlated with each other, we find negative or very small correlations across small firms and medium-sized firms, on the one hand, and large firms, on the other hand.

After that, we compute economic CRs and compare them with regulatory CRs. We find that (i) both CRs are increasing with firm size, (ii) for each size class, the level of the regulatory CRs is far superior to the level of the economic CRs, even after the application of the SF and (iii) the discrepancy between the economic CRs and the regulatory CRs becomes larger as firm size decreases. The higher values of the ratio of regulatory CRs to economic CRs for small size classes reflects an overestimation of SMEs risk relative to large corporates in the regulatory frameworks, even after taking into account the SF. Overall, after considering the uncertainty surrounding these estimates and adopting a conservative approach, we find strong evidence that the SF is consistent with the difference in economic CRs between SMEs and large corporates.

Regarding the *credit analysis*, we find evidence showing that the SF has been effective in supporting bank lending to targeted SMEs. First, we find that eligible exposures have increased by 5% to 10% on average as compared to ineligible exposures after the implementation of the SF (vs. before the reform) depending on the specification. In the most conservative estimation including group specific trends, we still find that the SF has boosted eligible exposures by 2%. This average effect is robust to various robustness checks. Then, we find that the magnitude of the effect of the SF has increased over time: the effect is almost zero in the first year after the entry into force of the SF but it has then intensified to reach a magnitude of 8% to 10% two years after the entry into force. At the same time, we do confirm that the trends of eligible and ineligible exposures did not diverge in a significant way before the reform. This test is an important validation of our empirical strategy based on the differences-in-differences estimator.

Concerning the possible sources of heterogeneity, we first find that the effect of the SF seems much stronger on eligible exposures of large SMEs (*i.e.* firms with a pre-reform turnover lower than €1.5 million) than on eligible exposures of small SMEs. Then, we find convincing evidence showing that exposures of SMEs with a good Banque de France credit rating tend to be more affected by the implementation of the SF than exposures of SMEs with a bad credit rating. These two results provide interesting insights regarding the effectiveness of the SF. On the one hand, the SF has not directed bank lending to the very small firms, those firms who are the most likely to face credit constraints and for which the marginal value of one additional euro of credit is probably the highest. But one the other hand, the SF has pushed banks to increase their lending relatively more to healthy borrowers (as reflected by the credit rating) what is highly desirable from a regulatory perspective.

Finally, our analysis reveals that the effect of the SF is non-linear. We inspect how the magnitude of the effect varies along with the size of exposures. We find that eligilbe exposures classified as small (*i.e.* exposures with an average outstanding amount of credit over the pre-reform period lower than €500,000) have strongly benefited from the SF. In contrast, medium and large eligible exposures have decreased (as compared to the ineligible exposures) in the post-reform period. This results can be rationalized once you consider the ambiguity surrounding the incentives provided by the reform. Since the SF applies to the total outstanding amount (*i.e.* the existing stock of credit) and not just to the new loans, not only banks can benefit from the SF without extending any additional loans but also, as increasing the outstanding amount of loans makes them closer to the threshold, the risk to pass above the threshold and, as a result, to lose the CRs discount on the total outstanding amount increases. Given that, banks may have incentives to limit the growth of exposures that are "too large", meaning those exposures that are originally in the vinicity of the threshold of eligibility. Our results are in line with this hypothesis.

Our paper relates to three strands of the literature. First, our work relates to the literature exploring empirically the relationship between CRs and lending. This relation has been recently reassessed exploiting both the strong capital shortfall induced by the financial crisis, the recent changes in regulation and an easier access to granular data that allows us to control for demand and supply shocks. Recent contributions tend to support a negative impact of higher CRs on credit distribution (Aiyar et al. (2014), Behn et al. (2016) , Jimenez et al. (2017) or Fraisse, Lé, and Thesmar (*forthcoming*)). In contrast to these studies that generally consider the impact of tighter CRs, our paper exploits a policy experiment explicitly designed to support credit growth through a targeted *decrease* in CRs. So far, this is the first study to the best of our knowledge that analyses the consequences of reduced regulatory CRs, which can provide a more comprehensive understanding of this relationship because there are no reasons to think that the effect is symmetric. For instance our results might provide guidance to macroprudential authorities, when relaxing macroprudential buffers targeting SME lending.

Our paper is also related to the literature about the risk assessment of banks credit portfolio. From the seminal work of (Merton, 1974) having shaped the credit risk structural approach, a lot of progress has been made regarding credit risk assessment. In particular, this approach underlies the Basel II/III regulatory capital requirements formula (Gordy, 2003). However, the Basel II/III regulatory formulas do not take into account borrowers' heterogeneity and possible concentration effects coming from potentially correlated defaults across borrowers whose financial situation is driven by "sectoral" systematic risk factors. We contribute to the existing literature by explicitly accounting for concentration/diversification effect using a multifactor framework where firm size acts as risk factors, a choice that is motivated by the SF issue.[7]

Lastly, the evaluations of the effectiveness of the SF are rather scarce. The only paper we are aware of is Mayordomo and Rodríguez-Moreno (2018). The authors assess the impact of the SF on the credit supply using mainly survey data for the Euro area (the SAFE survey). They also complete their analysis using the Spanish credit register. They find that the SF tends to alleviate credit constraint faced by medium-sized SMEs, but not for the micro and small SMEs. They interpret their result as indicating that banks prefer to grant loans to the safest SME companies to reach the regulatory requirements with the least risky commitment. We complement their analysis by estimating the effect of the SF using the French credit register on a much longer time period surrounding the implementation of the reform. Our analysis is nonetheless more comprehensive for several reasons. Firstly, our estimation of the effect of the SF is based on the differences-in-differences methodology while

[7]With respect to this strand of literature, our paper has also the benefit to exploit longer time series of default rates of SMEs.

they only run simple differences. This allows us to test important identifying assumptions and to control for preexisting differences between eligible and ineligible exposures. Moreover, we have a much longer time-serie and our results indicate that it matters for identification because the effect of the SF tends to materialize only one year after the entry into force of the reform. Second, we uncover non-linearities in the effect of the SF that raise questions about the design of the reform and its effectiveness on the largest eligible exposures. Third, we go one step farther in identifying separately the role of size and riskiness as a source of heterogeneity in the effect of the SF while they consider the size of firms as a proxy of their riskiness.

Overall, our paper contributes to these different strands of the literature, providing a new perspective, with both an analytic examination of the consistency of the CRs associated with SME risks and an empirical evaluation of the effective impact of the SF on the credit supply. The remainder of the paper is organized as follows: Section 2 presents the institutional background and the detailed definition of the SF. Section 3 describes the data and provides descriptive statistics. Section 4 details the methodology used for our empirical analysis. Section 5 is devoted to the presentation of our findings, some alternative specifications and related comments. Section 6 provides concluding remarks.

2 Institutional Framework

SMEs are generally considered as a key driving force for job creation and economic growth in Europe. Furthermore, bank credit is a crucial source of finance for SMEs (Beck and Demirguc-Kunt (2006)) and this is why bank lending to SMEs is a salient political issue in Europe.[8] In 2013, the European Commission assessed that the transition from Basel II to Basel III would lead to an increase in CRs from 8% to 10.5% for the average European bank. Against this background, the European legislator decided to introduce a deduction in the CRs for exposures to SMEs when transposing the Basel III standards into EU law.[9] This CRs deduction aims at offsetting the expected increase in CRs due to the transition from Basel II to Basel III for SMEs. It reflects the policy will and the general concern that SMEs should not suffer from the consequences of financial crises they are not responsible for. Therefore, under certain conditions, CRs associated with SMEs loans will be reduced by 23.81% [10] or subject to a so called *Supporting Factor* of 0.7619.

The regulation comes into force the 1st of January, 2014. The new regulation defines precisely the SMEs targeted by this CRs relief. Banks can alleviate their CRs for credit risk associated with a given exposure by multiplying these CRs by 0.7619 provided that[11] :

- the exposure is included either in the *retail*, *corporate* or *secured by mortgages on immovable property* regulatory portfolio
- the borrower/debtor is a firm with a turnover below €50 millions. (See Appendix 10.1 for more details about the definition of SMEs)
- the total amount owed to the institution and parent undertakings and its subsidiaries, including any exposure in default but excluding claims or contingent claims secured on residential property collateral, does not exceed €1.5 million. (See Appendix 10.1 for more details about the total amount owed to the institution)

Note also that :

- exposures in default shall be included for the purpose of determining the eligibility, but excluded from the application of the SF
- these precited criteria should be met on an ongoing basis

Overall, it is expected that the implementation of the SF leads banks to provide relatively more credit to eligible exposures/SMEs than to ineligible exposure/SMEs.[12] Indeed, for each

[8]"*SMEs are the backbone of the European economy, providing a potential source for jobs and economic growth*", European Commission, Regulation of the European Parliament and of the Council, 2015.

[9]See Article 501 of the Capital Requirements Regulation (CRR).

[10]The magnitude of this discount was calibrated from the anticipated increase in CRs for the average European bank : 1-8%/10.5%

[11]`https://www.eba.europa.eu/regulation-and-policy/single-rulebook/interactive-single-rulebook/-/interactive-single-rulebook/toc/504/article-id/4902;jsessionid=1BB645BAF83F701B15ABF1B26949F02A`

[12]Formally, a firm *per se* is not considered as eligible or ineligible. Only the exposures are deemed as eligible/ineligible. For instance, a given SMEs can be eligible to the SF with a given bank and, at the same time, ineligible with the other banks. For the sake of simplicity, in the present paper, we will nonetheless

additional euro of credit granted, the relative cost in term of CRs is 24% lower than before when this additional euro of credit is granted to eligible SMEs as compared to ineligible SMEs or to non-SMEs. At the margin, banks have thus incentives to increase their lending to eligible SMEs as compared to any other firms.

Nevertheless, as soon as 2014-Q1, the alleviation in CRs applies to the total outstanding amount of credit, and not just at the margin *i.e.* on newly granted loans. That means that any banks whose exposures are eligible will immediately benefit from a 24% discount in CRs on their actual stock of eligible exposures, whatever be their response to the reform. Consequently, we cannot exclude that banks also use the relaxation of capital constraints (resulting from the application of the SF to the (actual) outstanding amount of eligible credit) to provide more credit to non-eligible SMEs, to large companies or even to invest in other classes of assets that are far from the objective of improving credit supply to SMEs.

In this case, the ineligible exposures will also increase following the implementation of the Supporting Factor. However, if this is true, this mecanism acts as a downward bias in our estimation of the effect of the Supporting Factor. Said differently, it will make more difficult to find a positive effect of the SF in our setting as it will become clear in the very next section.

use indiscriminately the terms *eligible firms* and *eligible exposures.*

3 Data and Descriptive Statistics

3.1 The French credit register

We use the French national credit register maintained by the Banque de France (*"Centrale des risques"*). This register reports all the credits granted by any resident credit institution as well as some specific institutions like the *Sociétés de financement* (which are entitled to make credit but not to receive deposits on demand) or the investment firms providing credit. The population of borrowers/debtors includes any resident and nonresident legal entity (firms, local governments and administrations) as well as any natural person having a professional activity operating nationwide. Firms are defined here as legal units (they are not consolidated under their holding company when they are affiliated with a corporate group) and identified by a unique national identification number (called a "SIREN" number). They include single businesses, corporations, and sole proprietorships engaged in professional activities. A bank has to report its credit exposure to a given firm as soon as the total outstanding exposure on this firm is larger than €25,000. The credit register provides quarterly information regarding the type of credit granted among 12 distinct types of loan belonging to 6 broad categories (see Appendix 10.2).

The credit register also provides detailed information regarding the size and the creditworthiness of borrowing firms when they have a turnover above €0.75 million or a total outstanding amount higher than €380K. Indeed, the Banque de France estimates internally its own credit ratings for a large population of resident firms (about 300,000) and in particular for small firms that are generally not under the scope of the private rating agencies. The Banque de France has been recognized as an external credit assessment institution (ECAI) for its company rating activity. This enables credit institutions to rely on this Banque de France rating to calculate their regulatory capital requirements. The Banque de France has also been recognized as an ICAS - In-house Credit Assessment System - under the General Documentation governing the Eurosystem's monetary policy operations. Therefore, ratings are also used for refinancing bank loans in the Eurosystem Credit Assessment Framework (ECAF).

Both the credit and the risk analysis are run using this common dataset but they are subject to slightly different restrictions that we explain in the following subsections.

3.2 Risk analysis

Regarding the *risk analysis*, we restrict the sample to firms that have at least one exposure reported in the French credit register (see Appendix 10.3 for more details about the reporting requirement of this register). This population constitutes more than 3 million of observations over the period. We restrict the dataset to the years going from 2004 to 2015, *i.e.* 66 quarters, and to firms having a Banque de France rating. The sample is representative of the French businesses population. For instance, the Banque de France indicates that the database containing all accounting information used to assess the creditworthiness of firms (*Centrale de Bilans*, *Fiben*) represents at least 75% of the turnover of the population of French firms.[13]

Figure 1 depicts the evolution of the aggregate annual default rate over time (see the section 5.1 for additional details), together with real yearly GDP growth rate. It shows a clear dependency of the default rate to the business cycle, which justifies the assessment of risk through a systematic factor. Figure 2 illustrates the differences in the default rates across Banque de France ratings. As expected, we observe that firms with the lowest rating (the safest firms) have a lower default rate than firms with the highest rating (the riskiest firms).

3.3 Credit analysis

Regarding the *credit analysis*, we are no longer limited by the availability of the credit risk rating. We run the analysis over the period 2010-2016, *i.e.* 4 years before the entry into force of the SF (the *pre* period) and 3 years after (the *post* period). For the purpose of identifying eligible exposures, we aggregate them at the firm-banking group-quarter level using an auxiliary dataset allowing us to identify banking groups and their affiliates. As we suspect that the credit effect of the SF might be observed on very small firms, we do not restrict the sample to firms with available information regarding the Banque de France credit rating.

We limit our dataset to small and medium-sized enterprises (SMEs) and exclude large companies with a turnover higher than €50 million. The aim there is to contrast the most comparable firms, using the eligibility threshold as the main component of our differences-in-differences specification (more on this later). We could have included non-SME firms such that the eligibility criterium would have been two-folded: we could have compared SMEs and non-SMEs with an outstanding amount of loan lower than €1.5 million. We do not proceed in this way because firms with a turnover higher than €50 million are significantly different from SMEs, especially regarding their relation with bank lending (in particular, they have an easier access to a range of substitutes to bank credit). This is why we limit the sample to SMEs and we discriminate across them using the threshold for eligibility to the SF. We provide additional information about the restrictions made to the dataset in Appendix 10.4.

We also limit the sample of firms to *independent firms*. Indeed, in the regulation, it is not entirely clear whether the firm-level thresholds used to identify eligible firms have to be considered at the legal unit level or at the consolidated level. On top of that, anecdotical evidence indicates that banks have sometimes many difficulties to identify precisely the scope

[13]See Banque de France, 2016, *Rapport de l'Observatoire des delais de paiement*

of consolidation of companies. By limiting the sample to independent firms, we overcome this uncertainty.

As a result, we end up with an extremely large, unbalanced, dataset of more than 18.5 million of observations corresponding to 1,093,817 unique firms over 28 quarters. Overall, this dataset has several advantages. First, it can be considered as quasi-comprehensive given the low reporting threshold. We only miss few loans to very small firms that are economically insignificant at the aggregate level. Second, we have a long time series at a quarterly frequency. It thus covers a sufficient period before and after the implementation of the SF, which enables us to explore the effects of the reform while allowing banks to take time to react and adjust their lending (in contrast with Mayordomo and Rodríguez-Moreno (2018) who examine a very short period of time). Third, we have very granular information, even if we do not have a flow information (new credit issuance), but a stock information (outstanding credit amount). This information at the firm-bank-quarter level enables us to distinguish a given firm-bank pair through many dimensions (e.g. time series, cross-section, banking product) that we exploit in this paper.

3.4 Descriptive Statistics

Table 3 provides descriptive statistics regarding our dependent variable, the total outstanding amount of loans. In the first row, the sample includes firms whose eligibility status varies over the period of estimation. As explained in appendix 10.4, we drop these firms whose eligiblity status varies over the period. Thus, the second row displays the sample of firms whose eligibility status remains constant. Likewise, row (3) and (4) show descriptive statistics for the periods before and after the implementation of the SF, respectively. We can observe that the mean and the median values are of the same order of magnitude, indicating a consistency of the database that ensures accurate estimations.

Turning to the eligibility status, table 4 shows that the share of eligible exposures, which is very large (around 99%), is nonetheless constant over the 2 periods before and after the implementation of the SF. Again, this regularity is required to compare the two periods of estimation. MORE TO ADD ON THIS MAYBE

4 Empirical Strategy: methodology

4.1 Assessing the risk consistency of the Supporting Factor

To assess the consistency of regulatory CRs —including the SF– with SMEs intrinsic credit risk, we compare regulatory CRs with CRs computed by using a more comprehensive economic approach provided by a multifactor portfolio credit risk model[14]. This model grounds on the structural credit risk approach, as devoted by Merton (1974). In our implementation of this model, firm size acts as a systematic risk factor. Even if the regulatory formulas for corporate exposures introduce some adjustments related to firm size, the regulatory models do only consider a single general risk factor and they do not consider the impact of other systematic risk factors (Gordy, 2003).

It is important to emphasize why the multifactor model can be used as a benchmark to check the consistency of the capital deduction induced by the Supporting Factor on SMEs loans with the SMEs risk. Therefore, in this section, we first explain why the CRs measures derived from a multifactor framework can be used as benchmarks. Then, we provide a short description of the multifactor framework and describe how we apply it for our risk analysis.

4.1.1 The multi-factor model as benchmark for CRs measurement

There is a relationship between *regulatory CRs* and *economic CRs* derived from a multifactor model. The Basel II/III risk weight regulatory formulas were calibrated using the standard *Asymptotic Single Risk Factor* (ASRF) model (Gordy, 2003). In this framework, bank's total CRs are computed by using two parameters which refer to firm's individual risk, the probability of default (PD) and the loss given default (LGD), and a third parameter - the asset correlation R – which measures the sensitivity of borrowers to a common single systematic risk factor. So, regulatory Risk Weighted Assets (RWAs) are consistent measures of credit risk. However, two calibration choices determine potential differences between regulatory and economic CRs, which justifies to compare the two types of measures. Firstly, in the regulatory formulas, asset correlation R is entirely determined by the PD. But, as measures of the sensitivity of loans to a risk factor, they should in fact vary from one portfolio to another one, depending on its composition. In practice, Basel II/III regulation provides banks with the formulas to compute R, instead of leaving them computing this risk parameter using internal information. Consequently, a main difference between regulatory and economic CRs comes from the value of assets correlations. Secondly, in the ASRF model, there is only one single risk. However, borrowers' financial health is linked to multiple sources of credit risk which are more or less specific to the risk segment to which they belong. Consequently, risk measurement should account for borrowers' heterogeneity.

Taking account for borrowers' heterogeneity obliges to expand the standard single risk

[14]See Appendix 10.5 for more details about this methodology.

factor model and to adopt a multifactor framework. Moreover, a multifactor model allows the detection of potential concentration (diversification) effects coming from the strong (weak) dependence of borrowers to risk factors which are specific to their own risk segment. In case of realization of unfavorable value of one systematic risk factor, the number of defaults will increase and losses will climb to higher levels. In such a case, the contribution to the portfolio's segment which is exposed to this risk factor will raise, inducing an increase in total losses.

More generally, if the sensibility of exposures to the systematic risk factor which is specific to their segment is high, the relative contribution of this segment to the portfolio's total losses will be high, which corresponds to a situation of credit risk concentration in that segment. So, in a portfolio composed of several segments, using a multifactor model allows us to compute the marginal contribution of each segment to total losses and to observe either the impact of this segment on the concentration of losses or, on the contrary, the role the segment plays in the diversification of the portfolio credit risk.

In practice, this marginal contribution can be expressed under the form of a capital ratio by relating economic CRs needed to cover potential unexpected losses produced to this segment (computed at a given percentile - for instance 99.9 percent - of the probability distribution function of losses) to total exposures of the segment. In this way, we can assess portfolio's concentration and diversification in terms of capital ratio as a common metrics, showing how size factors could contribute to increase or decrease the level of CRs relative to the level given by a single risk factor model.

4.1.2 A short view of the multifactor model

The multifactor model we use in this paper belongs to the class of structural credit risk models.[15] It is an extended version of the ASRF model. The extension of the ASRF framework consists in introducing risk factors which can be linked to observable characteristics of borrowers and vary across groups of borrowers. As mentioned before, such an extension improves substantially the computation of the dependency structure across exposures in a loans portfolio, by allowing us to account for potential credit risk concentration which is linked to borrowers' heterogeneity. Here, we assume that firm size reflects the borrowers' heterogeneity and we expand the ASRF model by considering a latent risk factor for each size class.

To compute economic capital in this framework, we proceed in two steps. First, we compute portfolios' main risk parameters and in particular the dependence structure among exposures measured by the matrix of variance-covariance within each size class and between classes. Then, we use Monte-Carlo simulation to build the probability distribution function of losses, determine the total portfolio potential losses and compute the marginal contribution of each size class to potential losses, which measures the buffer of economic capital

[15] In the Appendix 10.5, we offer a complete and technical presentation of the model.

required to cover the losses in each size class.

To estimate risk parameters, we use an econometric model that belongs to the class of generalized linear mixed models (GLMMs) that combines fixed and random effects for observable and (latent) unobservable factors. Indeed, as shown by Frey and McNeil (2003) and McNeil and Wendin (2007a), the GLMM model implements in a coherent way the Merton latent factor default modeling approach, in which the default occurs when the value of the firm's assets become smaller than the value of its debt, that is, because firm's assets values are difficult to observe, when the value of a latent variable describing the financial situation of the firm - which depends on the realization of a set of risk factors - crosses an unobservable threshold which determines the default. In this framework, the default threshold is considered as the fixed effect of the GLMM. The systematic risk factors are supposed to be latent factors and then correspond to the random effects of the GLMM. Here, random effects are linked to the firm size segmentation of the portfolio.

Thus, in this framework, the default rate is modeled as :

$$P(Y_{ti} = 1|\gamma_t) = \Phi(x'_{ti}\mu_r + z_{ti}\gamma_t) \tag{1}$$

in which the default rate depends on i) a fixed effect measured by the borrower's internal rating μ_r, and ii) random effects γ_t which are related to a set of factors corresponding to the size segmentation of the portfolio. Taking firm's credit rating histories to build time series of rates of default by portfolio segments, we get estimates of portfolio's credit risk parameters in a multi-factor context. The GLMM model provides estimates of default thresholds considered as fixed effects and covariance matrixes of a set of latent random effects corresponding to the set of systematic size factors. The estimation of such parameters allows the computation of economic capital as buffer of losses.

Once the credit risk parameters are estimated, the distribution of losses at the portfolio level is computed by Monte Carlo simulations, with each simulated realization of the systematic risk factors being converted into a conditional default probability at the rating/size segment level and, finally, into conditional expected losses at the portfolio level. Various quantiles based on risk measures such as Value-at-Risk (VaR) can then be retrieved from the simulated distribution of portfolio-wide losses. The computation of the portfolio's value-at-risk (VaR) and marginal risk contributions are made by using a methodology proposed by Tasche (2009), which grounds on an importance sampling based simulation of expected conditional losses. This methodology has the advantage to take into account the impact of borrowers' heterogeneity on economic capital charges and capital allocation.

4.2 Identifying the effect of the Supporting Factor on credit supply

4.2.1 The differences-in-differences framework

To assess the effectiveness of the Supporting Factor regarding the provision of credit to SMEs, we rely on the *differences-in-differences* framework. In this setting, we compare a treated group composed of all individuals affected by the reform to a control group made of comparable individuals non-affected by the reform. In our case, the sample is made of French SMEs, *i.e.* firms with a turnover lower than €50 million (see the section 3 and appendix 10.3 for more details about the sample selection). The treatment group will then refer to exposures/SMEs eligible to the SF and the control group will refer to exposures/SMEs non-eligible to the SF.

As described in the section 2, a pair of bank-firm $\{b, f\}$ (or more precisely an exposure $\{b, f\}$) is considered as being eligible to the SF when the total *eligible* outstanding amount of credit from bank b toward firm f is lower than €1.5 million.[16] More precisely, we carefully dissociate the exposure used to assess the eligibility to the SF, denoted $\tilde{L}_{f,b,t}$, from the exposure that will benefit from the CRs deduction, denoted $L_{f,b,t}$.[17]

Starting from the first quarter of 2014, all exposures $L_{f,b,t}$ eligible to the SF (*i.e.* exposures where $\tilde{L}_{f,b,t}$ <€1.5 million) have immediately benefited from the 23.8% discount in CRs. We denote by $EL_{f,b,t}$ the variable that indicates the eligibility status of bank b when lending to firm f at quarter t:

$$EL_{f,b,t} = \begin{cases} 1 \text{ if } \tilde{L}_{f,b,t} \leq €1.5 \text{ million} \\ 0 \text{ if } \tilde{L}_{f,b,t} > €1.5 \text{ million} \end{cases} \tag{2}$$

However, under this definition, a pair of bank-firm $\{b, f\}$ may switch from the treated group to the control group (and *vice versa*) from one quarter to another as the amount $\tilde{L}_{f,b,t}$ used to assess the eligibility to the SF fluctuates over time. Hence, we are facing an important composition issue that could affect the stability of our treatment/control groups. To overcome this issue, we decide to keep only exposures $\{b, f\}$ whose eligibility status is stable over the whole period, *i.e.* we keep all exposures from pairs of bank-firms $\{b, f\}$ that are continuously eligible or ineligible to the SF over the entire period. We thus define $\bar{EL}_{f,b}$ as follow :

$$\bar{EL}_{f,b} = \begin{cases} 1 \text{ if } \tilde{EL}_{f,b,t} = 1 \ \forall \ t \\ 0 \text{ if } \tilde{EL}_{f,b,t} = 0 \ \forall \ t \end{cases} \tag{3}$$

[16]We could have included non-SMEs firms and the eligibility criteria would have been two-folded : we could have compared SMEs and non-SMEs with an outstanding amount lower than €1.5 million. We do not proceed in this way because we think that firms with a turnover higher than €50 million are very different from SMEs, especially regarding their relation with bank lending (in particular, they have access to a lot of substitutes to bank credit). This is why we limit the sample to SMEs and we classify them as treated/non-treated according to the eligibility threshold.

[17]See Appendix 10.1 for more details about the differences between the two quantities.

This restriction is rather conservative and does not threaten our identification strategy. Indeed, the restriction that we impose leads to exclude (i) eligible exposures that would become at some point ineligible and (ii) ineligible exposures that would become eligible at some point. In the first case, these are fast-growing "treated" exposures that pass above the €1.5 million threshold at some point. Ignoring them tends to reduce the intensity of the response of the treated to the treatment. In the second case, these are likely to be exposures classified in the control group that tends to decrease significantly over time until they pass below the threshold. By ignoring them, the control group as a whole has a dynamics more favorable than it would be otherwise. In both case, this restriction creates a downward bias in our identification strategy, *i.e.* it makes more difficult for us to detect an effect of the SF.[18]

We finally denote by $Post_t$ the variable indicating the period where the SF has entered into force:

$$Post_t = \begin{cases} 1 \text{ if } t \geq 2014Q1 \\ 0 \text{ if } t < 2014Q1 \end{cases} \tag{4}$$

4.2.2 The baseline specification

The goal of the *credit analysis* is to test whether the entry into force of the SF in 2014-Q1 has fostered credit supply of banks to eligible SMEs (as compared to ineligible SMEs). For this purpose, we estimate the following classical differences-in-differences specification :

$$ln(L_{f,b,t}) = \alpha + \beta \cdot \bar{E}L_{f,b} \cdot Post_t + \gamma \cdot \bar{E}L_{f,b} + \theta \cdot Post_t + \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \tag{5}$$

where:

- $L_{f,b,t}$ refers to the total outstanding amount of loans granted to the firm f by the bank b at the quarter t
- $\mu_{b,t}$, ω_b, and ρ_f denotes respectively bank-time fixed effects, bank fixed effects and firm fixed effects (FEs)

In these regressions, the coefficient of interest is β. It indicates to which extent the credit supply evolves differently for eligible pairs of bank-firms $\{b, f\}$ relative to ineligible pairs of bank-firms $\{b, f\}$ after the implementation of the SF compared with the pre-implementation period. We gradually saturate the regressions with firm, bank and time fixed effects to control for possible confounding factors. In some specifications, we even include bank-time fixed effects to control for bank funding shocks among other things (think to the TLTRO

[18] Alternatively, we could be tempted to classify exposures based on their status in the pre-reform period. However, in doing so, we would have created an upward bias. Indeed, in this case, we could misclassify an exposure as "treated" in post (because it is truly a "treated" exposure in pre) while it is not. Such an exposure would have grown significantly between the two periods. As a result, we would have overestimated the dynamics of the group of treated exposures. The opposite is true for the exposures classified in the control group.

for instance). In all regressions, we systematically control for the Banque de France rating and the size of the firms as well as their industrial sector and their geographic location. We cluster our standard errors at the firm level, *i.e.* we allow for some dependency in the standard errors *within* firms but we consider that these standard errors are i.i.d *across* firms (Abadie et al., 2017).

4.2.3 Dynamics over time and firm characteristics

Testing the parallel trends assumption We identify the effect of the SF on the credit supply using a differences-in-differences framework. An important identifying assumption of the differences-in-differences setting is the *parallel trends assumption*. We could test this identifying assumption by running a dynamic version of the baseline specification 5. Rather than identifying the effect of the SF on the entire post-reform period (as compared to the pre-reform period), we now estimate the differences in the (log of) outstanding amount of credit between eligible and ineligible pairs of bank-firm $\{b, f\}$ *within each quarter*. The specification writes as follows :

$$\begin{aligned} ln(L_{f,b,t}) = \;& \alpha + \textstyle\sum_t \beta_t \cdot \bar{EL}_{f,b} \cdot \mathbb{1}_t + \sum_t \gamma_t \cdot \bar{EL}_{f,b} + \sum_t \theta_t \cdot \mathbb{1}_t + \\ & \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \end{aligned} \tag{6}$$

where $\mathbb{1}_t$ denotes a dummy taking the value of 1 in quarter t and zero otherwise. The set of coefficients $\{\beta_t\}$ estimates the effect of the SF on the provision of credit within each quarter t. We thus expect to find the $\{\beta_t\}$ to be indistinguishable from zero for any quarter t in the pre-implementation period. In this case, we can conclude that the conditional dynamics of the credit received by eligible and ineligible exposures $\{b, f\}$ are not significantly different in the pre-reform period, *i.e.* our setting satisfies the parallel trends assumption.

By constrast, we expect to find the $\{\beta_t\}$ to be significantly positive for any quarter t in the post-implementation period. Above all, this specification is also very informative regarding the dynamics of the reform : does the magnitude of the effect tend to increase over time or, in constrast does this effect overshoot and then fade out after several quarters?

Heterogeneity and firm characteristics We then investigate to which extent the magnitude of the effect of the SF varies along with firm characteristics. We examine three dimensions: (i) the size of the firm, (ii) the riskiness of the firm and (iii) the size of the exposure. For this purpose, we run slightly modified versions of the specification 5. First, firms are sorted according to their size and their riskiness.[19] We define a firm as :

- $Risky_f$ when its Bank of France rating is above or equal to the notch 6 (which is considered as "very poor")
- $Safe_f$ when its Bank of France rating is below the notch 6

[19] More details about the Bank of France rating scale we use can be found here

– $Unknown_f$ when its Bank of France rating is equal to the notch 0 ("*No unfavourable information gathered*")

Then, we define a firm as :

– $Large_f$ when its turnover is higher than €1.5 million but below €50 million

– $Small_f$ when its turnover is lower than €1.5 million

We define these variables based on the characteristics of firms in the pre-reform period because both size and riskiness of firms can be affected by their indebteness. However, the size and the creditworthiness of firms are likely to vary from one quarter to another. Rather than using the value at a specific quarter in the pre-reform (2013-Q4 for instance), we prefer to take the *mode* of the size and the riskiness, *i.e.* we classify the firm as *small* or *risky* based on the size bucket and the Banque de France rating that are the most frequent in the pre-reform period. By doing so, we nonetheless lose few observations.[20]

Finally, we also classify pair of bank-firm according to the size of their exposure. In particular, we classify a pair of bank-firm $\{b, f\}$ as :

– $Small_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is lower than €500,000

– $Medium_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is comprised between €500,000 and €1 million

– $Large_{b,f}$ when the average pre-reform total "eligible" outstanding amount of credit is comprised between €1 million and €1.5 million

After that, to test each of these sources of heterogeneity, we run a generic specification where we interact all the terms of the baseline equation 5 with the various dummy variables built just before[21]:

$$\begin{aligned} ln(L_{f,b,t}) = \; & \alpha + \textstyle\sum_k \beta_k \cdot \bar{EL}_{f,b} \cdot Post_t \cdot \mathbb{1}_{Type=k} + \sum_k \gamma_k \cdot \bar{EL}_{f,b} \cdot \mathbb{1}_{Type=k} + \\ & \textstyle\sum_k \theta_k \cdot Post_t \cdot \mathbb{1}_{Type=k} + \mu_{b,t} + \omega_b + \rho_f + \epsilon_{b,f,t} \end{aligned} \tag{7}$$

These specifications allow us to test whether the magnitude of the effect of the SF is stronger or weaker depending on (i) the size of the firm f, (ii) the riskiness of the firm f, as measured by the Banque de France rating and (iii) the size of the exposure between bank b and firm f.

[20] In the case where the firm has two values for the mode, we ignore the firm

[21] For instance, $k \in \{Small; Large\}$.

5 Results

5.1 The effect of the Supporting Factor on bank risk portfolio

To assess the consistency of regulatory CRs for SMEs, and by the way the effectiveness of the SF, we compare, for each size class, the ratio of CRs measured when using the multifactor model parameters with the ratio of CRs given by the regulatory Basel II/III formulas. The economic CRs are computed by using the multifactor risk model presented above. They measure the marginal contributions of the different firm size classes to the total potential losses on a comprehensive bank business loans portfolio. The multifactor model provides a more comprehensive measure of portfolio credit risk, taking into account the borrowers' heterogeneity and possible concentration or diversification effects coming from the interactions between systematic risk factors associated to firm size classes. Thus the comparison between the two types of CRs provides an information about the possible over(under)estimation of effective credit risk by the regulatory formula and the possible compensation provided by the SF.

Recall that, in order to estimate the model, we built a portfolio containing the sum of the business loans held by French banks on each firm registered in the French Credit Register. To compute rate of defaults and other portfolio risk parameters by size classes, we used each firm's history of quarterly ratings (including default) in the ratings system of the Banque de France. To compute CRs, we assume a 45% Loss Given Default (LGD) and a 99.9% quantile of the probability distribution function of losses. These parameter values are those we find in the Basel II/III regulatory framework.[22] All models are estimated using annual default rates. Since we are ultimately concerned with the calibration of CRs, we consider not only the credit risk parameters estimates but also CRs dependent on these estimates. More precisely, we compare in each size class the ratio of CRs measured when using the multifactor model parameters with the ratio of CRs given by the regulatory Basel III formulas.

In this section, we first assess the level of sensitivity of firms to systematic risk, depending of their size, and the potential for diversification across size segments in the portfolio. The table 1 displays the random effect variances –which measure the exposure to systematic risk– and the correlations of the random effects –the correlations between size systematic risk factors –provided by the GLMM model.[23] More precisely, it shows that the largest firms are the most exposed to systematic risk, *i.e.* are the most exposed to general economic conditions, even if their default rates are low. Additionally, a joint equality test across random effects variances rejects the null hypothesis. Moreover, the random effects across

[22]The 45% are the LGD that were used in the so-called Basel II fondation approach that the banks could use in absence of a validated LGD model but with a validated PD model

[23]The estimation also yields 25 (5x5) default thresholds, not shown here for the sake of simplicity. As expected, these thresholds are ordered, reflecting the increasing likelihood of default for lower ratings, and statistically different from 0.

the classes of medium-sized and large firms are highly correlated, with correlations ranging between 95% and 100%. However, correlations across small firms and medium-sized, on the one hand, and large firms, on the other hand, are negative or very small, showing a potential for diversification effects between these size classes. Finally, what appears clearly from the results of the estimation is the potential for diversification provided by the presence of exposures on SMEs in the total bank loans portfolio.

The computation of economic CRs at the size level allows taking into account all different estimated dimensions of credit risk in a consistent way. Table 2 allows to compare the value of the economic CRs with the level of the regulatory CRs, under two regulatory regimes: the standard Basel II/III IRB regime and the CRD IV/CRR regime including the SF impact.[24] The table 2 shows an increasing relationship between size and the three distinct CRs, reflecting the growing sensitivity to systematic risk factor (a general factor in the regulatory models, the size risk factor specific to each size class in the economic model) with firm size. Moreover, the level of the two regulatory CRs is far superior to the level of the economic CRs, showing a potential overestimation of CRs by the Basel II/III regulatory formulas or the CRD IV/CRR regulatory formulas with a Supporting Factor. Here, we consider the CRs on large corporates (*i.e.* corporates with a turnover of more than €50 million) as a benchmark, which could be motivated by the fact that the SF introduces a deduction of CRs for SME loans with respect to the lack of deduction of CRs for larger corporates. We compute the ratios of the two regulatory CRs relative to the economic CRs (last two columns of table 2).

The comparison of the values of these ratios between size classes allows us to determine whether the size dependence of the regulatory CRs is consistent with that of the estimated economic CRs. The results confirm that the higher values of the ratios for small size classes reflect an overestimation of SMEs risk relative to large corporates in the two regulatory

[24]Under the Basel II/ III regime the regulatory CRs (for exposures on corporate) is computed accordingly to the following formula :

$$RW = \left(LGD \cdot N \left[(1-R)^{-0.5} \cdot G(PD) + \left(\frac{R}{(1-R)} \right)^{0.5} \cdot G(0.99) \right] - PD \cdot LGD \right) \cdot (1-1.5 \cdot b)^{-1} \cdot (1+(M-2.5) \cdot b) \cdot 12.5 \cdot 1.06 \tag{8}$$

where:

$$R = 0.12 \cdot \frac{(1-e^{(-50 \cdot PD)})}{(1-e^{(-50)})} + 0.24 \cdot \left(1 - \frac{(1-e^{(-50 \cdot PD)})}{(1-e^{(-50)})} \right) - 0.04 \cdot \left(1 - \frac{min(max(5,S),50)-5}{45} \right) \tag{9}$$

and

$$b = \left(0.11852 - 0.05487 \cdot ln(PD)\right)^2.$$

RW denotes the risk-weight or the capital requirements, R the correlation, b an adjustment factor, S the total annual sales in millions. PD the probability of default, LGD, the loss given default, M the maturity, $N(x)$ is the cdf of a normal distribution $N(0,1)$ and $G(z)$ is the reciprocal of this cdf. Under the CRD IV/CRR regime, the RW is multiplied by the Supporting Factor for the eligible firms. For a conservative approach, every firm of a size class is given the upper bound of the turnover sales. For instance, firms belonging to the [€7.5M-€15M] class are given a €15 million annual total sale. A similar IRB formula is provided for exposure on "other retail", *i.e.* on firms with exposures lower than €1.5 million.

frameworks. In addition, the results also show the CRs reduction provided by the implementation of the Supporting Factor. The ratio of the regulatory CRs to the economic CRs is lower for the CRD IV/CRR model than for the Basel II/III model. But, despite this reduction of the CRs, the ratio of regulatory CRs to the economic CRs still remains largely higher for SMEs than for large corporates. Notice that the last row of table 2 (called "all") shows the diversification benefits provided by the existence of exposures on different size classes within the same portfolio. The row corresponds to the weighted average of the different size classes CRs. It shows that the weighted average value of the economic CRs (3.2%) is far below the value of economic CRs for the large corporate (6.3 %), thanks to the presence of SMEs exposures less demanding in CRs in the loans portfolio. This saving in CRs is smaller for the regulatory CRs, the regulatory model failing to account for diversification benefits.

There is obviously some model uncertainty in economic CRs measurement. To deal with this issue, we use the values of random effect variance displayed in table 1 and we inflate the estimates of the random effect variance of the SME by two standard deviations [25] and we reduce the estimate for the large corporate by two standard deviations (0.225-2*0.07615=0.0727). With this new set of random effects, we compute both the economic CRs and the Basel II/III regulatory CRs. We find a ratio regulatory CRs to economic CRs of 9.10% for SMEs and of 6.47% for large corporates. In order to have the same economic CRs for SMEs and for large corporates as for the regulatory ratio, SMEs should benefit from a 71% discount which is very close to the SF calibration (76%).

In sum, economic CRs computations do confirm that the CRs should be lower for SMEs. According to a multiple factor economic capital framework, the SF should be much higher than 25% in order to be consistent with the difference in economic capital between large and small firms. Nevertheless, taking into account uncertainty surrounding the estimates of the multifactor models and adopting a conservative approach, the SF is consistent with the difference in economic capital between SMEs and large corporates.

5.2 The effect of the Supporting Factor on the credit supply

As explained in the econometric framework described in section 4.2, we assess the average effect of the SF on the distribution of credit by banks by relying on the *differences-in-differences* specification 5. With this specification, we compare the (log of) total outstanding amount of credit of eligible exposures vs. ineligible exposures in the post-reform period (as compared to the pre-reform period). After analyzing the impact of the SF on the average exposure/firm, we implement the other tests detailed in section 4.2.3 in order to provide a comprehensive overview of the impact of the SF.

[25] For illustration : 0.0723+2*0.03602=0.1443 for the [€15M-€50M] size class, 0.0163+2*0.0144=0.0451 for the [€5M-€15M] size class and so on...

5.2.1 The average impact of the Supporting Factor on the credit distribution

Table 5 presents the results associated with the baseline specification 5. The dependent variable is the logarithm of the total outstanding amount of credit between bank b and firm f at time t. As a result, we could interpret the estimated coefficient as a semi-elasticity. Importantly, we only consider the effect of the SF at the *intensive margin*, *i.e.* the effect of the SF on existing and positive bank-firm relationship. In a future version, we will explore the effect of the SF at the *extensive margin*, *i.e.* the effect of the SF on the creation/destruction of new bank-firm relationships.

We gradually include a set of fixed effects (FEs) in the regressions. We start with a set of quarter, location, industry and size FEs. The result can be found in column (1). Then, we introduce bank, bank-quarter and firm FEs. The role of the bank-quarter FEs is to control for bank funding shocks among other things. For instance, in the case where (i) some banks face a positive funding shock in the post-reform period and (ii) these banks have credit portfolios biased toward small eligible exposures, we could observe a positive coefficient $\hat{\beta}$ but for reasons unrelated to the SF. The results are shown in columns (2) to (4). In column (5), we even include size-quarter FEs to control for all the shocks specific to a given firm size class as it is a crucial dimension of the SF.

The point estimate ranges from 0.043 to 0.095 indicating that, when an exposure is considered as eligible to the SF, it receives on average between 4.3% and 9.95%[26] more credit than ineligible exposures in the post-reform period as compared to the pre-reform period. The fact that we rely on the differences-in-differences approach represents an improvement over Mayordomo and Rodríguez-Moreno (2018). Indeed, in their paper, they only consider simple differences between eligible and ineligible exposures. They only use the period preceeding the reform to run a falsification test but never estimate the effect of the SF using double differences.

In the last column, we include linear group-specific time trends. This allows treatment and control groups to follow different trends in a limited but potentially revealing way. With this specification, the effect of the SF is now identified through a *relative deviation* from the group-specific trends. Not suprisingly, the magnitude of the point estimate decreases but remains nonetheless sizable and significant (+1.8%). Importantly, we have enough quarters in the pre-reform period to identify accurately the trends from the period preceeding the reform (Wolfers, 2006). Overall, we found that the average exposure between bank b and firm f increases by 2% to 10% more after the introduction of the SF when the exposure is eligible to the SF than when it is not.

Robustness tests In order to ensure the robustness of this finding, we perform additional tests that are presented in the table 6. In the first column, we remove exposures with an average outstanding amount comprised in [€1M–€2M]. Indeed, as the exposure gets closer

[26]See Kennedy (1981) on how to interpret accurately semi-logarithmic elasticity with a dummy variable

to the threshold, the incentives for banks are increasingly mixed. At the margin, banks still have incentives to provide more credit to eligible exposures as compared to ineligible exposures. However, the bank has to make sure that the exposure will never pass above the threshold because it will then lose the 24% discount on CRs associated with the total outstanding amount of credit. This will provide strong incentives to limit the growth of exposures as they approach the threshold. This is why we remove exposures higher than €1M and lower than €2M where the incentives for banks to extend credit are mixed.[27] The effect is now identified by comparing exposures below €1M (eligible) with those above €2M (ineligible). We continue to observe a sizable effect of the SF (+6%).

Then, in column (2), we remove exposures just around the threshold, *i.e.* exposures with an average outstanding amount comprised in [€1.4M–€1.6M]. Indeed, we suspect that the outstanding amount of credit we observe in the credit register and the regulatory definition of exposures may not be perfectly aligned. Alternatively, banks may experience difficulties in identifying the total outstanding amount of a given counterpart at the group level on an ongoing basis. In either case, this could give rise to some misclassification. To avoid this issue, we estimate the effect of the SF after removing exposures around the threshold: the main finding remains unchanged.

In column (3), we adress the classical serial correlation issue (Bertrand et al., 2004) by collapsing the dataset into two periods (pre and post). After that, we rerun the baseline specification and still found a positive and significant effect of the SF. In column (4) we drop firms whose size (as reported by the Banque de France) is unknown. These are generally very small firms and ignoring them does not affect the initial finding. In column (5), we remove the two quarters surrounding the entry into force of the SF. This is particularly important in the case where banks tend to anticipate a bit the reform. We continue to observe a significant effect of the SF. Finally, in our last robustness check in column (6), we estimate the effect of the SF on a perfectly balanced sample. Said differently, all pairs of bank-firm $\{b, f\}$ have now a positive exposure all along the period studied (2010Q1-2016Q4). We lose a lot of observations but we now have perfectly stable groups over time. This is a way to avoid any composition effect. We observe that the estimated effect of the SF remains unchanged.

5.2.2 Dynamics of the effect over time and the parallel trend assumption

The differences-in-differences estimator hinges on a crucial assumption: the fact that the treated group and the control group have similar trends in the outcome variable throughout the period preceeding the reform. We can test this assumption by estimating a dynamic version of the baseline specification in which we estimate the effect of the SF *within* each

[27] At the same time, regarding exposures slightly *above* the threshold, banks may have incentives to let the exposures diminish as the loan is amortized in order to benefit from the 24% discount on CRs once the exposure falls below the threshold of eligibility.

quarter. Above all, this regression is informative regarding the dynamics of the effect over time : have banks responded immediately to the reform or, on the contrary, has the SF become increasingly effective quarter after quarter ? Has the effect of the SF on the credit supply persisted over time or has the initial impulse faded out after few quarters (for instance, as a result of the uncertainty surrounding the nature of the reform : temporary or permanent) ?

To answer these questions, we run the specification 6. Rather than presenting the numerous coefficients in an extended table, we plot the results in the figure 3. In this figure, we represent the coefficients estimated within each quarter as well as the corresponding 95% confidence bands. We define the reference period as 2014Q1 and materialize it with the vertical black line. All the coefficients must be interpreted with respect to this reference period. The underlying regression includes time, location, industry, size, rating, bank, firm and bank-quarter FEs.

First, we do not observe significant differences between the eligible and the ineligible exposures in the period before the reform. Except for few quarters where the difference between the control and the treated group is marginally significant at the 5% level (albeit negative), the figure reveals that the two groups have similar dynamics in the pre-reform period. This is a validation of the common trends assumption. Second, when we look at the post-reform period, we observe that the effect of the SF on the credit supply is not distinguishable from zero for the first four quarters following the entry into force of the SF. However, starting from 2015-Q1, the dynamics of the outstanding amount of credit received by eligible and ineligible groups tends to diverge increasingly and significantly. Said differently, the effect of the SF tends to be stronger over time. In 2016, the magnitude of the effect lies between 5% and 10%, at a much higher level than the baseline estimate.

5.2.3 Heterogeneity of the effect of the SF

We now investigate in more details to which extent the effect of the Supporting Factor varies along with firm/exposures characteristics. We focus on three dimensions : the size of firms, their riskiness (as measured by the Banque de France rating) and the size of the exposure. We run the generic specification 7 using these three dimensions one after another. The results of these tests are presented in the tables 7 and 8.

Firm characteristics In the first column of the table 7, we test whether the SF has the same effect on eligible exposures from large and small firms. For that purpose, we classify firms as large or small according to their size classes reported in the credit register and based on the turnover of firms. Then, in the second column of the table 7, we test the magnitude of the effect of the SF on the provision of credit by banks depending on the riskiness of firms. We classify the firms as safe or risky according to their Banque de France rating.

As explained in the section 4.2.3, we classify a firm as large or risky according to the most frequent value observed in the pre-reform period. By doing so, we want to avoid endogeneous feedback loops where the response to the SF affects the size or the riskiness of the firm. Indeed, a firm receiving relatively more credit is likely to grow faster or to have an increasing leverage. Both of these mechanisms would affect the size or the riskiness of firms.

The result of this first test in column (1) is unambiguous. While eligible exposures from small firms grow by 3% (as compared to ineligible exposures), the eligible exposures from large firms grow by 9% (as compared to ineligible exposures). The effect of the Supporting Factor is three times larger for firms with a turnover higher than €1.5M than for firms with a turnover lower than €1.5M. This finding is constistent with those of Mayordomo and Rodríguez-Moreno (2018). Using the *Survey on the Access to Finance of Enterprises*, they found that "*the SF alleviates credit rationing for medium-sized firms that are eligible for the application of the SF but not for micro/small firms*". However, in their analysis the authors take firm size as a proxy for firm riskiness and conclude that "*this finding is in line with the fact that micro/small firms are riskier than medium firms, and hence, they are not treated equally to medium-sized firms by banks.*". Interestingly, we are able to analyse separately the size and the riskiness of firms thanks to the Banque de France credit rating. As a result, we can push the analysis further.

The result of the second test in column (2) is less clear-cut. We observe that the effect of the SF on exposures from firms classified as risky strongly diverges from the effect of the SF on exposures from firms deemed as safe or from firms for which the Banque de France has "*no unfavourable information gathered*". The effect is even negative in the case of risky firms, *i.e.* eligible exposures from those firms tend to decrease as compared to ineligible exposures. Regarding the two other categories of firms, we do not find significant differences between them: the effect of the SF is estimated to be around 5%. This result indicates that eligible exposures from risky firms tend to diminish after the implementation of the SF while eligible exposures from safe firms (or those with "no unfavourable information gathered") are targeted by banks when responding to the SF.

The two results are consistent but they nonetheless convey different information : indeed, among the firms that we classify as *risky*, 95% of them are firms that we classify as *small*. However, among the firms classified as small, 15% of them are also classified as risky. This proportion is just 5% for medium or large firms but the vast majority of small firms are not considered as risky.

Non linearities Our third test is slightly different. Rather than contrasting the effect of the SF with respect to firm characteristics, we now explore how the effect of the SF differs depending on the size of the exposure. Say differently, we test for non linearities in the effect of the SF on the credit supply. The rationale behind such a test comes from the fact that, as explained before in the paragraph 5.2.1, as the outstanding amount of credit associated with the pair of bank-firm $\{b, f\}$ approaches the threshold of eligibility, the incentives given to banks by the SF becomes increasingly ambiguous. On the one hand, it is still relatively less costly in terms of CRs to lend to eligible pair of bank-firm at the margin but on the other hand, the risk to pass above the threshold (and therefore to lose the CRs discount on the *total* outstanding amount of credit) increases at the same time. Consequently, as the exposure gets closer to the threshold, banks may become increasingly reluctant to extend additional credit to the relevant firms.

As a result, we expect that the effect of the SF should become proportionally weaker as the size of the exposure increases. Given that the coefficient of interest β indicates an effect of the SF in relative terms, the coefficient associated with the largest eligible exposures could even become negative, indicating that these exposures have decreased (as compared to ineligible exposures) after the implementation of the SF.

To implement this test, we classify exposure according to their average outstanding amount computed over the pre-reform period as explained in the section 4.2.3. We define three buckets : *small* ([0-€500,000]), *medium* ([€500,000-€1M]) and *large* ([€1M-€1.5M]). Then, we estimate simultaneously a coefficient β for each of these three buckets using the generic specification 7. This test is in line with the identification strategy implemented by Mayordomo and Rodríguez-Moreno (2018). However, we favor a *discrete* functional form while they use a *continuous* functional form.

The results of this test can be found in the table 8. We report several specifications including various fixed effects. We observe that the coefficient associated with exposures categorized as *small* is systematically positive and significant while the coefficient associated with the two other buckets of exposures (*medium* and *large*) are significantly negative: as compared to the ineligible exposures, the eligible exposures considered as *small* tend to grow more after the entry into force of the reform (between +9% and +15%) while this is not the case for *medium* and *large* eligible exposures. We even observe that the *medium* and *large* exposures tend to decrease in the post-reform period.

These results confirm that banks have primarily supported exposures of small size as a result of the implementation of the Supporting Factor. This finding can be rationalized if we consider that the design of the SF provides ambiguous incentives. This ambiguity comes from the fact that the SF does not target flows of new credit but rather provides a CRs relief on the existing stock of credit. As a result banks may benefit from the SF without any action being required on their part. Around the threshold of eligibility, banks may even have incentives to curb credit growth in order to avoid passing the threshold and losing the CRs relief on the total outstanding amount of credit. This last hypothesis is consistent with our results: the exposures classified as *medium* or *large* tend to decrease (in relative terms) after the entry into force of the SF. To the best of our knowledge, we are the first to highlight this drawback in the design of the Supporting Factor and to provide evidence showing it. Note that the current Commission's proposal to maintain the Supporting Factor and to extend its scope with no upper limit[28] is a way to resolve this drawbacks of the current scheme.

Overall, we find that the effect of the SF is highly heterogeneous and that not all SMEs with eligible exposures have benefited from its implementation. Our findings show that the SF have mainly benefited to large and safe SMEs with rather small exposures. While the first result indicates that the SF has not be very effective for the smallest SMEs, the firms that are presumably the most credit constrained as a result of asymetry of information and those for which a marginal euro of additional credit has the highest value, the second result provides a more optimistic view regarding the effectiveness of the SF : banks have directed their lending to the healthiest borrowers.

[28]More specifically, above the €1.5 million limit, a 15% reduction for the remaining part of the exposure would apply.

6 Conclusion

This paper investigates the effectiveness and the consistency of a new regulatory tool implemented specifically to promote SMEs' access to bank credit: a targeted reduction in bank CRs associated with SMEs loans. In particular, the objectives of this reform are to provide an easier access to bank credit for SMEs and to ensure adequate capital requirements for SME credit risk. That is why we examine this policy experiment along with these two dimensions.

First, the consistency of the reform regarding the intrinsic riskiness of SMEs is gauged through the computation of banks' economic capital requirements using the structural credit risk framework underlying the computation of the regulatory capital requirements. This method allows us to compute the contribution of each size class to the total risk of the portfolio, taking into account the potential diversification or concentration effects within the portfolio. We finally compare the "economic" CRs resulting from our multifactor model with the regulatory ones, with and without considering the reduction associated to the SF. We find that for each size class, the level of the regulatory CRs is far superior to the level of the economic CRs, even after the application of the SF. Overall, after considering the uncertainty surrounding these estimates and adopting a conservative approach, we find strong evidence that the SF is consistent with the difference in economic CRs between SMEs and large corporates.

Then, the impact of the reform on the credit supply to targeted SMEs is estimated through the differences-in-differences methodology. We thus compare the evolution of the outstanding amount of credit of eligible and ineligible exposures after the reform (vs. before the reform). We find evidence showing that the SF has been effective in supporting bank lending to targeted SMEs. Specifically, we find that the magnitude of the effect of the SF has increased over time: the effect was almost zero in the first year after the entry into force of the SF but it has then intensified to reach a magnitude of 8% to 10% two years after the entry into force. Concerning the possible sources of heterogeneity, results indicate that the effect of the SF is much stronger on eligible exposures of large SMEs than those on small SMEs. Then, we find convincing evidence showing that exposures of SMEs with a good Banque de France credit rating tend to be more affected by the implementation of the SF than exposures of SMEs with a bad credit rating. Finally, we find that the smallest eligible exposures benefited the most from the SF, encouraging the withdrawal of the eligibility threshold at €1.5 million. These results provide interesting insights regarding the effectiveness of the SF. On the one hand, the SF has not directed bank lending to those very small firms who are the most likely to face credit constraints and for which the marginal value of one additional euro of credit is probably the highest. Nevertheless, on the other hand, the SF has pushed banks to increase their lending relatively more to healthy borrowers what is highly desirable from a regulatory perspective.

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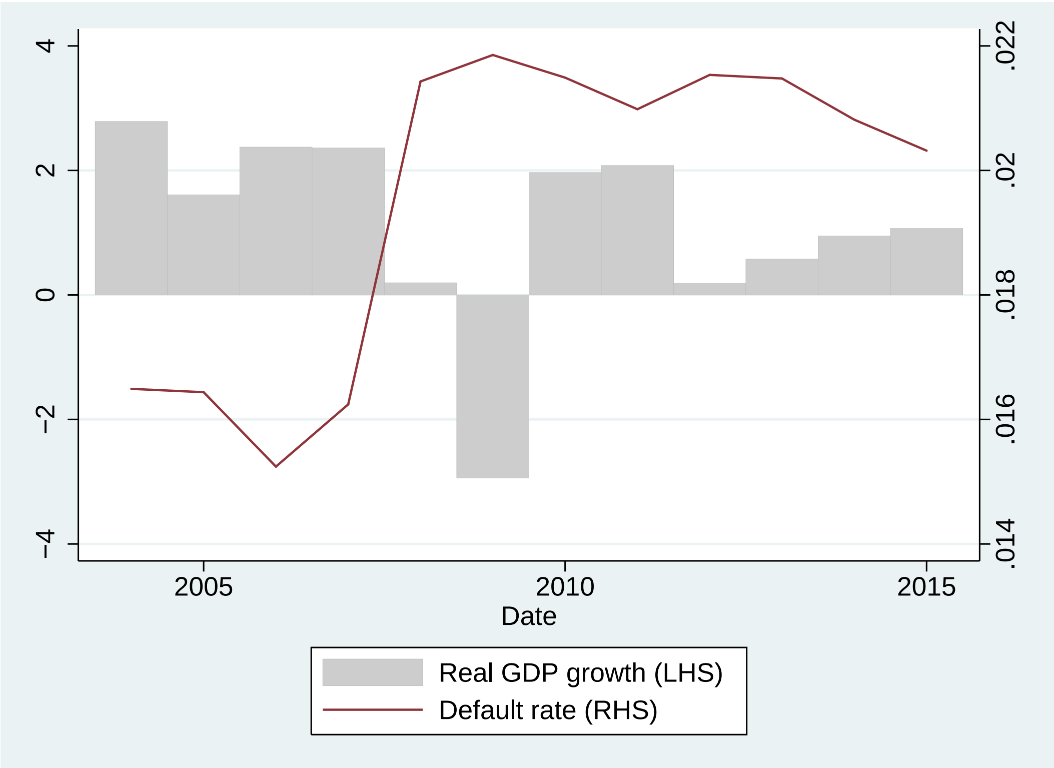
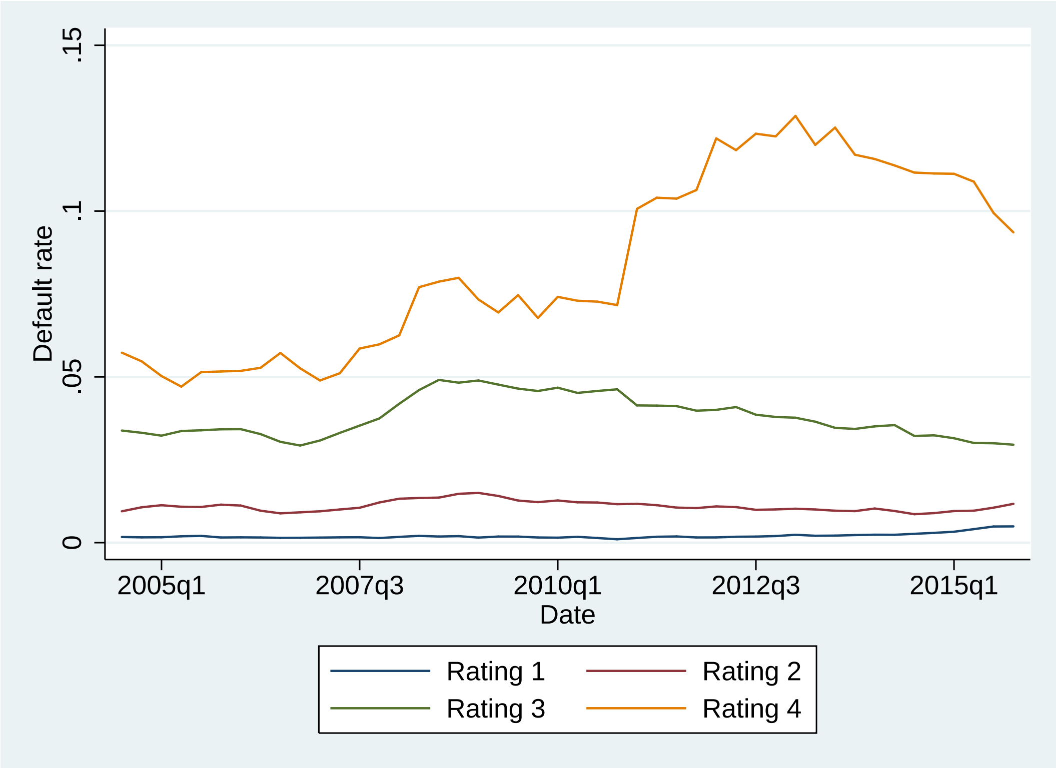
8 Figures

Figure 1: Default rates over time (all size and rating) and change in real GDP



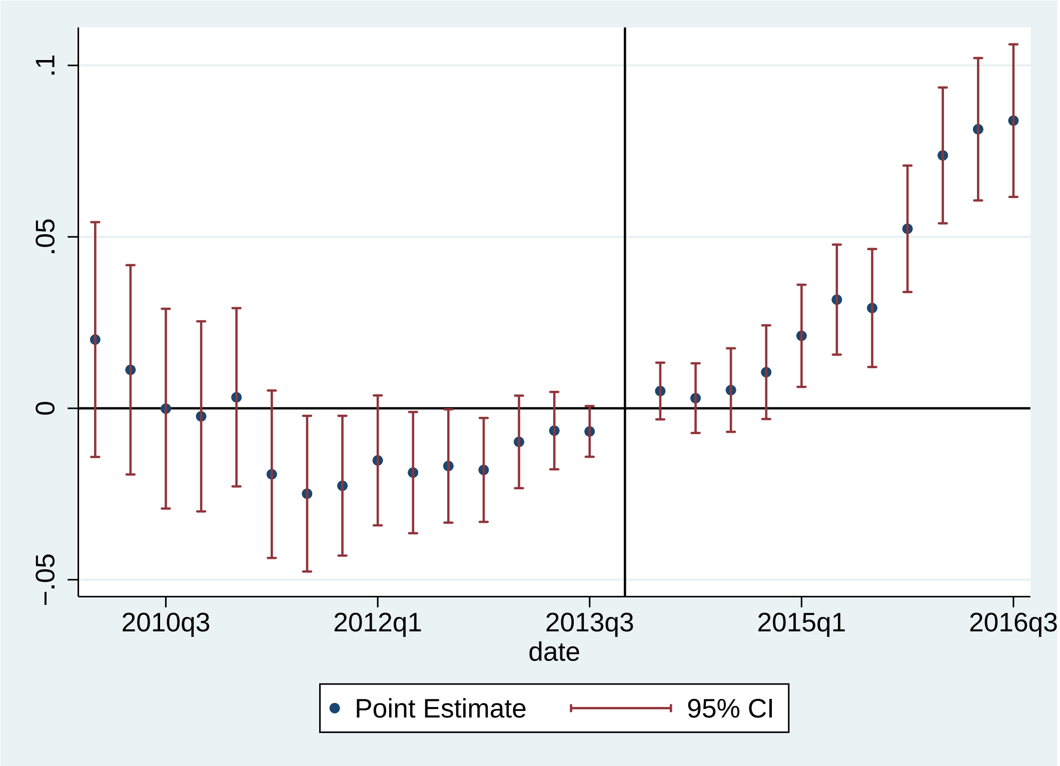
Note: This figure shows semi-annual changes in real GDP (LHS axis) and the total default rate (RHS axis) expressed as a percentage for the years 2004 to 2015 for France. The default rate is defined as the fraction of firms either filing for bankruptcy or defaulting on trade credit. The sample is made of firms operating in France with a yearly turnover larger than €750K and a credit exposure larger than €25K. The sample of banks or foreign bank subsidiaries operating in France is exhaustive.
Source: Banque de France, authors' calculations.

Figure 2: Default rates (in %) over time (all size classes, by rating)



Note: This figure shows the default rates for the years 2004 to 2015. The panel depicts the default rates for rating categories 1 (the safest category) to 4 (the riskiest category) for France. Rating categories for French exposures are defined thanks to the official rating given by the Banque de France department of businesses. These ratings are used as eligibility criteria to the refinancing operation of the Eurosystem. The default rate is defined as the fraction of firms either filing for bankruptcy or defaulting on trade credit. The French sample is made of firms operating in France with a yearly turnover larger than €750K and a credit exposure larger than €25K. The sample of French banks or foreign bank subsidiaries operating in France is exhaustive.
Source: Banque de France, authors' calculations.

Figure 3: The effect of the SF on the credit supply: dynamics over time



Note: This figure shows the estimates associated to the differences-in-differences specification 6. This specification assesses the effect of the SF on credit supply to SMEs quarter after quarter. The blue dots refer to the point estimates associated with the difference in credit distribution between eligible SMEs and ineligible SMEs within each quarter. The red bars indicate the 95% confidence intervals associated with these point estimates. The vertical line indicates the implementation of the SF reform, in January 2014. The underlying econometric specification controls for size, rating, department and industry classes, as well as year-quarter FEs and it includes bank, bank-time and firm FEs.
Source: Banque de France, authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

9 Tables

Table 1: Random effects variances and correlations

Panel A: Random effects variances (%)					
	Retail		*Corporate*		
Size Class:	$[0.75-1.5]$	$[1.5-5]$	$[5-15]$	$[15-50]$	$[>50]$
Estimates	0.0094	0.0034	0.0163	0.0723	0.225
Standard Errors	0.0101	0.0012	0.0144	0.0360	0.0762

Panel B: Correlation matrix of random effects

Size Class:	$[0.75-1.5]$	$[1.5-7.5]$	$[7.5-15]$	$[15-50]$	$[>50]$
$[0.75-1.5]$	1				
$[1.5-7.5]$	0.6454	1			
$[7.5-15]$	-0.5802	0.2520	1		
$[15-50]$	-0.7361	0.04326	0.9721	1	1
$[>50]$	-0.7698	-0.04406	0.9519	1	1

This table shows the estimated variances of the random effects and their correlation matrix. All parameters in Table 1 are significantly different from 0 with p-values lower than 1%.
Source: Banque de France, authors' calculations.

Table 2: Annual economic and regulatory capital ratios (CR) by size tranches (%)

Size Class	Economic CRs (1)	Regulatory CRs (2)	Regulatory CRs with SF (3)	Ratio (2)/(1)	Ratio (3)/(1)
$[0.75 - 1.5]$	0.83	6.2	5.2	7.5	6.3
$[1.5 - 7.5]$	1.1	9.8	7.5	8.9	6.8
$[7.5 - 15]$	1.7	9.8	6.7	5.8	3.9
$[15 - 50]$	3.2	9.4	5.4	2.9	1.7
$[> 50]$	6.3	10.2	10.2	1.6	1.6
All	3.2	9.5	7.5	3.0	2.4

This table shows the value of capital ratios when using the multifactor model (economic capital) and the regulatory Basel III model or the regulatory CRD IV/CRR model taking into account the supporting factor (SF). For the regulatory models, we used the *IRB other retail* formula for the computation of assets correlation in the smallest size class [0.75-1.5], and the *IRB corporate* formula (with the corresponding size-turnover-adjustment) for the four last classes of medium and large enterprises.
Source: Banque de France, French national Credit Register and authors' calculations.

Table 3: Descriptive Statistics : Distribution of the outstanding amount of loan

N	Mean	SD	P10	P25	Median	P75	P90
Sample including firms whose eligibility status changes over time							
1.86e+07	145.40	247.37	0.00	25.00	36.00	70.00	154.00
Sample of firms whose eligibility status is constant over time							
1.84e+07	130.97	195.50	0.00	25.00	36.00	69.00	149.00
Before the implementation of the SF							
1.04e+07	129.19	192.84	0.00	25.00	36.00	68.00	147.00
After the implementation of the SF							
7 977 413	133.30	198.88	0.00	25.00	35.00	69.00	151.00

This table provides descriptive statistics on our dependent variable, the total outstanding amount of loans. The samples described are before and after the implementation of the SF.
Source: Banque de France, French national Credit Register and authors' calculations.

Table 4: Descriptive Statistics

Eligibility Status	Frequency	Percent
	Before the implementation of the SF	
Non eligible (Exposures > €1,5M)	17.437	0.17
Eligible (Exposures < €1,5M)	10,374,235	99.83
Total	10,391,672	100.00
	After the implementation of the SF	
Non eligible (Exposures > €1,5M)	17.907	0.22
Eligible (Exposures < €1,5M)	7,959,506	99.78
Total	7,977,413	100.00

This table shows the distribution of eligible and non eligible exposures, for the two periods before and after the implementation of the SF.
Source: Banque de France, French national Credit Register and authors' calculations.

Table 5: The effect of the SF on the credit supply

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible · Post	0.087***	0.095***	0.094***	0.043***	0.067***	0.018**
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.007)
Observations	16,331,261	16,331,261	16,331,261	16,275,264	16,275,264	16,275,264
Adjusted R-squared	0.174	0.178	0.178	0.733	0.733	0.733
Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Size*Time FE	No	No	No	No	Yes	Yes
Group-specific trends	No	No	No	No	No	Yes

This table reports the estimates associated with the differences-in-differences specification 5. The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total "eligible" outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable of interest *Eligible* · *Post* is the product of these two latter dummies. All regressions control for size, rating, geographic location and industry classes, as well as year-quarter FE. Column (1) displays results associated with these most basic FEs. Columns (2) to (6) display estimates including gradually bank, bank-time, firm, size-time FE and group-specific trends. Regressions are clustered at the firm level. Clustered standard errors are reported in brackets.

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

Source: Banque de France - ACPR, French national credit register and authors' calculations.

Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

Table 6: The effect of the SF on the credit supply: robustness checks

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible · Post	0.059***	0.044***	0.029**	0.036***	0.063***	0.051***
	(0.010)	(0.010)	(0.014)	(0.010)	(0.012)	(0.011)
Observations	16,214,490	16,274,136	1,665,354	8,930,159	13,808,816	5,144,383
Adjusted R-squared	0.728	0.733	0.583	0.697	0.727	0.787
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Avg exp. in [0;1000[& [2000-5000[	Avg exp. in [0;1400[& [1600-5000[	Collapse into 2 periods	Drop firms with unknown size	Drop quarters in [2013Q3-2014Q2]	Balanced sample

This table reports the estimates associated with the differences-in-differences specification 5 on various subsamples. The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total "eligible" outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable of interest *Eligible* · *Post* is the product of these two latter dummies. In column (1), we run the differences-in-differences estimation on a subsample excluding pairs of bank-firm with an average outstanding amount of credit between €1M and €2M. Column (2) estimates the effect of the SF on a subsample excluding pairs of bank-firm with average outstanding amount of credit between €1.4M and €1.6M. Column (3) reports the coefficient of interest after collapsing the data into 2 time periods (pre and post) to overcome serial correlation issues. Column (4) reports our estimations on a subsample excluding firms whose size (turnover) is unknown. Column (5) reports estimations after dropping the period surrounding the implementation of the SF, *i.e.* from 2013Q3 to 2014Q2. Finally, column (6) shows estimates based on a perfectly balanced sample, *i.e.* we keep all pairs of bank-firm b, f that have a positive exposure over the entire period considered (2010Q1-2016Q4). All regressions control for size, rating, geographic location, industry, bank, bank-time, firm, as well as year-quarter FEs. Regressions are clustered at the firm level. Clustered standard errors are in brackets.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Banque de France - ACPR, French national credit register and authors' calculations.

Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

Table 7: The effect of the SF on the credit supply: breakdown by firm's characteristics

	Logarithm of the total outstanding amount of credit	
	(1)	(2)
Eligible · Post · *Large*	0.088***	
	(0.016)	
Eligible · Post · *Small*	0.029**	
	(0.012)	
Eligible · Post · *Risky*		-0.030***
		(0.026)
Eligible · Post · *Unknown*		0.052***
		(0.012)
Eligible · Post · *Safe*		0.061***
		(0.016)
Observations	15,050,896	16,275,264
Adjusted R-squared	0.723	0.733
Bank FE	Yes	Yes
Bank*Time FE	Yes	Yes
Firm FE	Yes	Yes
T-test small vs large (p-value)	0	
T-test risky vs unknown (p-value)		0
T-test safe vs unknown (p-value)		.67

This table reports the estimates associated with the differences-in-differences specification 5. The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total eligible outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable *Eligible · Post* is the product of these two latter dummies. We interact this last variable with 2 characteristics of the firms: the size as measured by the turnover and the riskiness as assessed by the rating provided by the Banque de France. Firms are classified according to the most frequent value observed in the pre-reform period. We distinguish the riskiness of the firms according to their rating in 3 classes: risky, non-rated and safe. Likewise, we distinguish the size of the firms in 2 classes: small and large. All regressions control for size, rating, geographic location, industry, bank, bank-time, firm, as well as year-quarter FEs. Regressions are clustered at the firm level. Clustered standard errors are in brackets.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

Table 8: The effect of the SF on the credit supply: breakdown by exposure buckets

	Logarithm of the total outstanding amount of credit					
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible · Post · *Small*	0.155***	0.159***	0.157***	0.059***	0.092***	0.038***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.006)
Eligible · Post · *Medium*	-0.116***	-0.112***	-0.118***	-0.127***	-0.112***	-0.074***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.006)
Eligible · Post · *Large*	-0.151***	-0.149***	-0.153***	-0.159***	-0.149***	-0.036***
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.008)
Observations	16,544,487	16,544,487	16,544,487	16,488,568	16,488,568	16,488,568
Adjusted R-squared	0.362	0.365	0.365	0.768	0.768	0.768
Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank*Time FE	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Size*Time FE	No	No	No	No	Yes	Yes
Group-specific trends	No	No	No	No	No	Yes

This table reports the estimates associated with the differences-in-differences specification 5. The dependent variable is the logarithm of the total outstanding amount of credit. The dummy *Eligible* denotes SMEs whose total eligible outstanding amount of credit is lower than €1.5M. The dummy *Post* denotes the period after the implementation of the SF in 2014. The variable *Eligible* · *Post* is the product of these two latter dummies. This variable is interacted with 3 buckets of exposures: Small, Medium and Large. *Small* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [0-€500,000]. *Medium* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [€500,000-€1,000,000]. *Large* exposures refer to exposures with an average pre-reform total outstanding amount of credit in [€1,000,000-€1,500,000].
All regressions control for size, rating, geographic location and industry classes, as well as year-quarter FEs. Column (1) displays results associated with these most basic FE. Columns (2) to (6) display estimates including respectively bank, bank-time, firm and size-time FEs as well as group-specific trends. Regressions are clustered at the firm level. Clustered standard errors are in brackets.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Banque de France - ACPR, French national credit register and authors' calculations.
Sample: Independent SMEs that borrow from one of the 7 main French banking groups over the period 2010-2016.

10 Appendix

10.1 Institutional framework of the Supporting Factor reform

Definition of SMEs for the purpose of the Supporting Factor

The identification of SMEs is precisely defined by the 2003 European Commission Recommendation as follows: "*The category of micro, small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250 persons and which have an annual turnover not exceeding €50 million or an annual balance sheet total not exceeding €43 million.*" Among these criteria, the CRR indicates that only the annual turnover must be considered to qualify a company as an SME allowed to benefit from the SF.

Conditions of eligibility

Regarding the amount "owed" to the institution, the CRR also brings precisions about exposures eligible to the SME-SF. In the case of a credit line, only the drawn amount must be considered as regard to the €1.5 million compliance limit. However, provided that all conditions are met, the exposure as a whole, including its undrawn part will benefit from the capital relief. Thus, there exists a discrepancy between (i) the exposure amount considered for the eligibility to the SF and (ii) the exposure amount that will benefit from the CRs deduction (SF enforcement). Practically, off-balance sheet exposures and claims or contingent claims secured on residential property collateral must not be considered when assessing the amount owed and eligible to the SF. Though, the SF, as deduction in CRs, applies to the entire bank's exposure.

10.2 French national credit register: breakdown by loan type

- Short-term loans (i.e. with an initial maturity shorter than 1 year)
  - Overdrafts on ordinary account (including short term credit line drawdown)
  - Accounts receivable financing
  - Factoring
  - Other short-term loans
- Medium and Long-term loans (i.e. with an initial maturity longer than 1 year)
  - Export credits
  - Other medium and long-term loans
- Financial Leases and Leasing
  - Equipment leases
  - Property leases
- Securitized loans
- Undrawn credit lines
  - Undrawn loans (of which factoring available)
  - Opening of documentary credit
- Guarantees commitments

10.3 Risk analysis: data restrictions

This appendix reports more detailed information about the databases used in the *risk* analysis. To do that, we need to restrict the sample of firms to the following conditions:

- Firms must have exposures in the French credit register. In France, every bank should declare business loans provided that the loan amount is over €25,000 starting from 2006. However, before 2006, this threshold was €75,000. To avoid creating artificial entries of firms in 2006, we apply the €75,000 threshold over the entire sample period considered, *i.e.* 2004-2015.
- The Banque de France rating directorate gives to these firms a rating (including a default grade). That means that firms' annual turnover is above €0.75 million and firms obtain credit from at least one large banking group operating in the French loans to businesses market.
- We also exclude exposures toward the financial sector. Indeed, we neutralize a break related to the end of the reporting of interbank exposures with non-resident counterparts in 2006.
- We exclude exposures toward individual entrepreneurs. They stopped reporting their exposures within the credit register in 2012, so we drop them from the total sample to avoid artificial exits of the sample.

10.4 Credit analysis: data restrictions

This section reports more detailed information about the databases used in the *credit* analysis. To do that, we need to restrict the sample to the following conditions:

- We restrict the sample to the 7 largest banking groups operating in France. The other credit institutions of the sample are very specific credit suppliers that do not reflect the bank lending in France. We thus keep the following banking groups: BNP-Paribas, Société Générale, BPCE, Crédit Agricole, Crédit Mutuel, HSBC, la Banque Postale, which represents 90% of the corporate lending market.
- Firms are restricted to SMEs according to the sole turnover criterium, *i.e.* we only keep firms with an annual turnover lower than €50 million. As mentioned above, the identification of SMEs can be tricky. For instance, 80% of legal entities constituted by 50 employees belong to a larger group. Therefore, to avoid any misclassification of companies, we restrict the sample to independent firms only, *i.e.* firms that are not affiliated with a corporate group.
- We exclude exposures toward the financial sector, the real estate sector, the public sector and the non-profit sector. We also drop holding companies.
- We exclude exposures toward individual entrepreneurs. They stopped reporting their exposures within the credit register in 2012, so we drop them from the total sample.
- In order to run clean specifications, we drop firms whose SME status or eligiblity status vary over the period. There, the aim is to keep firms for which the status remains constant over time (additional information on this important point can be found in the section 4.2).

10.5 Risk analysis: the detailed methodology

The computation of banks portfolio risk under the Basel regulatory framework derives from the structural credit risk approach proposed by Merton (1974). We use an extended version of this approach in order to assess the risk increase induced by the SF. In this section we provide a short description of this framework and describe how we apply it for our risk analysis.

In the Merton (1974) framework, losses at the sub-portfolio level are defined as the sum of losses on defaulting loans. Thus, if u_i is defined as the loss given default (LGD) of obligor i and Y_i is the default indicator variable of obligor i (Y_i takes the value of 1 if there is a default and 0 otherwise), total portfolio losses L are given by

$$L = \sum_{i=1}^{n} u_i Y_i \tag{10}$$

where n denotes the number of obligors.

In structural credit-risk models, default occurs if the financial health of borrower i crosses a default threshold. Here, financial health is represented by a latent (unobservable) variable U_i, which is determined by the realizations s of a set of S multivariate Gaussian systematic risk factors with loadings w_i and correlation matrix R, and the realization of a standard normal specific factor ε_i. Denoting Φ the standard normal cdf, default occurs when U_i crosses downwards a threshold. This threshold is calibrated from the borrower's historical default probability $\bar{p_i}$:

$$Y_i = 1 \Leftrightarrow U_i = w_i' S + \sqrt{1 - w_i' R w_i} \varepsilon_i < \Phi^{-1}(\bar{p_i}) \tag{11}$$

Specific risk factors ε_i are assumed to be uncorrelated among obligors and also independent from the systematic factors S. The factor loading can be interpreted as the sensitivity of the obligor i to systematic factors or more commonly expressed as the general macroeconomic state of the economy.

Thus, given a realization s of the systematic risk factors, Equation (2) can be rewritten such as a default occurs when:

$$\varepsilon_i < \frac{\Phi^{-1}(\bar{p_i}) - w_i' s}{\sqrt{1 - w_i' R w_i}} \tag{12}$$

As the borrower's specific risk factor is normally distributed, the default probability conditional to s is also standard normal. Moreover, assuming that specific risk can be entirely diversified away, losses can be approximated by their expected value conditional to s (see Gordy (2003)). Conditional portfolio losses are then defined by:

$$L(s) \approx \sum_{i=1}^{n} u_i \Phi \left[\frac{\Phi^{-1}(\bar{p_i}) - w_i' s}{\sqrt{1 - w_i' R w_i}} \right] \tag{13}$$

This framework is known as the asymptotic multi-factor framework of credit risk (see Lucas et al. (2001)) and is an extension of the asymptotic latent single risk factor (ASRF) model underlying the Basel II CRs for credit risk. Equation (4) assumes that each obligor can be characterized by his individual default threshold and factor sensitivities. However, in retail loan portfolios, default rates are generally computed based on rating grades, and sensitivities to risk factors cannot be computed on an individual basis. Thus, assumptions are required to reduce the number of parameters of the loss variable. A common assumption is that obligors who belong to the same rating j will share the same default threshold. Moreover, one could assume that the vector of risk factor sensitivities is the same for obligors sharing a set of common characteristics. Assuming that the portfolio is portioned in K segments (here the firm size), that credit exposures are rated using a scale with J grades, and denoting n_{kj} the number of exposures with rating j in segment k, losses can be rewritten as:

$$L(s) \approx \sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{n_{kj}} u_i \Phi\left[\frac{\Phi^{-1}(\bar{p_j}) - w_k' s}{\sqrt{1 - w_k' R w_k}}\right] \tag{14}$$

The calibration of this credit risk model requires the estimation of J default thresholds $\Phi^{-1}(\bar{p_j})$ of the rating scale, the factor loadings w_k, and the correlation matrix R. A first order choice is the specification of the systematic risk factors. However, we are interested in capturing the risk heterogeneity for firms of different sizes. Thus, we expand the latent factor approach underlying the ASRF model by considering a latent risk factor for each size class. These factors are possibly correlated, with correlation matrix R. In other words, we consider that credit risk within each portfolio size segment can be described by a single risk factor model, taking into account correlations of risk exposures across segments. The different parameters are estimated using a binomial probit generalized linear mixed model (see McNeil and Wendin (2007b)). The generalized linear mixed model (GLMM) provides a straightforward econometric framework to estimate the parameters of our multifactor credit risk model. Indeed, the choice of this specification leads to consider the default thresholds as fixed effects and the factor loadings and factor correlations as described by a multivariate vector of Gaussian random effects.

Within the framework of GLMM models, the default probability in equation (5) is defined as follows. Let Y_t be an $(N \times 1)$ vector of observed default data at time t and γ_t be the $(K \times 1)$ vector of random effects. The conditional expected default probability of obligor i at time t is then:

$$P(Y_{ti} = 1|\gamma_t) = \Phi(x_{ti}'\beta + z_i\gamma_t) \tag{15}$$

where $\Phi(.)$ is the standard normal cdf [29], β denotes the vector of parameters associated

[29] We focus on the probit link function because the normal distribution is the underlying link function that is assumed by the Basel II/III framework of credit risk.

with the fixed effects (the borrower's rating class) and z_i is the design matrix of the random effects, here an identity matrix with size the number of random effects. If the rating scale is properly built, we expect the β parameters that correspond to the default thresholds to be associated with the ratings to be ordered and to increase as credit quality decreases. $x'_{ti} = [0, ..., 1, ..., 0]$ is a $(1 \times J)$ vector of dummies defining the rating of borrower i at time t.

Once the credit risk parameters are estimated, the distribution of losses at the portfolio level is computed by Monte Carlo simulations, with each simulated realization of the systematic risk factors being converted into a conditional default probability at the rating/size segment level as defined by Equation (5) and, finally, into conditional expected losses at the portfolio level. Various quantiles based on risk measures such as Value-at-Risk (VaR) or Expected Shortfall can then be retrieved from the simulated distribution of portfolio-wide losses.

Our multifactor model provides the economic capital necessary to cover losses of a portfolio of loans by firm size buckets. We use this model as a benchmark to check whether the capital deduction induced by the supporting factor on SME loans (about 24%) is consistent with the difference in economic capital between the SME loans and the rest of the corporate loans portfolio (the "large" corporate businesses).