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Regulating the banking sector to support credit access: Evidence from small business

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Abstract

This study investigated the effectiveness of regulatory interventions in mitigating the harmful effects of financial crises on small firms. We examine the impact of a support factor implemented by European policymakers on Italian micro-, small-, and medium-sized enterprises (MSMEs) between 2007 and 2017. The analysis uses a difference-in-differences approach to assess the credit conditions of these firms. Contrary to expectations, our results show that MSMEs in Italy continue to face credit constraints even after the introduction of the support factor. In contrast, we find that structural factors and portfolio effects play a more important role in promoting favorable credit conditions for small firms. Our results highlight the importance of considering these factors in conjunction with regulatory interventions to achieve better outcomes. This study has implications for policymakers and stakeholders, particularly in assessing the appropriateness of extending support factors for different policy purposes.

1 | INTRODUCTION

In addition to having a system stability purpose, can banking regulations also be designed to produce a stimulus for economic growth in general through easier and more efficient access to credit for small and medium-sized enterprises? In 2013, precisely to maintain the stability of the financial system and ensure the continuity of credit in times of crisis, the European Commission introduced a supporting factor (SF) for micro, small, and medium enterprises (MSMEs) designed to mitigate the cost of bank capital on the credit provided to these counterparties. The rationale for the policy measure is described in European Banking Authority (2016). The intervention was further strengthened in 2020 after the pandemic crisis and the related difficulties of companies and more recently with the introduction of a green supporting factor that adjusts the capital requirements for "green" financial instruments.

This study estimates the impact of financial policy decisions oriented toward credit support. Because the measure introduced in Europe by policymakers resulted in a structural break, we use statistical techniques to estimate the impact of the program, with robustness tests useful to determine whether and how MSMEs, and indirectly the economic system, benefited from the new regulatory environment. The measure aimed to stabilize the business cycle according to the correlation between the contribution of bank credit supply and real gross domestic product (GDP). However, these objectives do not always seem compatible.

The impact analysis also implies that the empirical exercise conducted where the target companies are addressed plays a highly significant role. Therefore, we analyzed the impact of SF in Italy. Italy is a particularly relevant laboratory when analyzing the problem of access to credit for MSMEs for at least two reasons. The first factor is the degree of dependence on bank credit. As Hoffmann et al. (2022) show, Italy has the lowest rate of bond and equity issuances by firms. The second reason is the weight that MSMEs assume in the economic context. Regarding the contribution of MSMEs[1] to aggregate value added, European Union (EU) countries show high heterogeneity, ranging from 47% in Germany to 69% in Italy (Papadopoulos et al., 2018). As MSMEs have relatively lower credit quality than large firms, the risk for banks in countries where smaller firms are predominant has increased. One consequence is greater credit tightening for structurally fragile firms such as MSMEs, particularly in countries most affected by economic slowdowns. This bank-corporate link generated a short circuit between the real and financial crises, especially in countries that showed little resilience to shocks. To ensure bank support for nonfinancial firms, the authorities changed the regulations and prevented financial system stability by inducing a credit crunch with negative economic externalities.

Our empirical tests adopt a difference-in-differences (DiD) design. All firms classified as MSMEs in our sample period (2007–2017) are considered treatment firms. The year in which the introduction of the MSME SF exerted its effects was the year of the event. The control firms are large; that is, those excluded from the effects of the regulatory measure. Therefore, any difference in the dependent variable between the treatment and control firms after the introduction of SF can be attributed to its effectiveness. Since the assumption of the measure adopted by European policymakers is that there is a relationship between the magnitudes affected by SF, access to credit, and, although indirectly, the credit economy, the objective is to assess whether this assumption is confirmed empirically, as well as to understand in what terms this implies similar effects when using a similar measure for other objectives, such as redirecting financial flows towards sustainable projects and enterprises.

Our results show that the introduction of the policy measure had economically insignificant effects on MSMEs' credit access constraints. However, if the trend of our dependent variable for MSMEs differed from that of large firms, the critical assumption of parallel trends underlying our DiD design would be violated. We conducted a dynamic test to investigate this issue and ensure the validity of the results. The results show no significant difference in the trend of the intersecting variable between the treatment and control firms before the SF; thus, the critical hypothesis of parallel trends underlying our DiD design is fulfilled. This evidence suggests that SF did not have the hoped-for effects on MSMEs' ability to access credit. To further strengthen the robustness of the results and the validity of our DiD design, we conducted a placebo (falsification) test, which showed no significant difference in the variable estimating access to credit.

Since capital absorption depends on two factors, the capital ratio and risk-weighted assets (RWA), acting on only one of the factors (in this case, the first) does not necessarily guarantee that the final result (i.e., the product of the two factors) is the desired result. Therefore, based on the empirical results presented in this article, we argue that the main reason for the greater constraints on MSMEs' access to credit than those of large firms is that an additional and more relevant factor conditioning choice in the lending process, namely, the diversification benefit obtained through correlations between assets in the banking book, has not been corrected. As they are drawn by regulations, the correlations that banks must consider in the portfolio model predict that they will benefit: (a) smallest versus largest; (b) worst-rated versus best-rated firms. The current regulatory scheme commits a two-fold error when compared with the empirical evidence of credit correlations observed in several countries, including Italy. First, it does not attribute the real and greater benefit of diversification of credit portfolios, because the correlations are significantly lower than the regulatory ones. Second, it artificially directs credit towards the worst-rated firms when the lowest correlations are observed precisely among the best-rated firms.

In particular, this article highlights how banks' behavior has been induced to adverse selection by a regulation that does not grasp, at least in relation to credit correlations, the right element of diversification that would lead to easier access to credit for the best-quality MSMEs. This aspect is particularly relevant in Italy, where microenterprises make up more than 80% of the MSME category, but also applies to other countries with a similar distribution of enterprises by size.

We find that, overall, MSME lending did not receive a boost with the introduction of SF, and that, paradoxically, the quality of portfolios deteriorated. Our analysis sheds light on the differences implicit in the Basel formulae between the capital requirements of MSMEs and large firms, and their empirical justification in the data from a risk management perspective. Our results suggest that structural and portfolio factors are more relevant in promoting better credit access for MSMEs. Thus, the empirical results suggest the need to rethink the incentive architecture designed by European policymakers and stimulate the supply of credit to MSMEs through regulatory solutions designed according to RWAs and the correlations observed in credit portfolios. This topic is not only important to assess the effectiveness of an instrument introduced in Europe a few years ago but is also crucial in the current debate to understand how the banking system and its regulation can be part of the solution to the economic crisis caused by the pandemic and possibly be adopted by non-European countries.

The remainder of this paper is organized as follows. We introduce the background of the related literature in Section 2. We then show how to construct the measurement of the "tied borrower" and show the characteristics of the data. The main empirical results are presented in Section 3. In Section 4, we examine how our results relate to past and future policy decisions to improve access to credit for MSMEs after a crisis. Section 5 concludes.

2 | LITERATURE REVIEW

A large body of the literature supports the importance of capital and credit support in bank regulations, although it draws mixed conclusions. A key issue highlighted by the global financial crisis was the regulators' approach to resolving banking and market turmoil. The main criticism of the regulatory framework before the last global financial crisis was that it was "essentially" microprudential in nature (Borio, 2003). Although the banking system is characterized by a high degree of heterogeneity and fragmentation, the way and speed with which the financial crisis spread and infected the entire banking system has shown that such an approach to resolving a financial crisis is ineffective because it aims to prevent the bankruptcy costs of an individual financial institution.

The contagion risk that materialized with the latest financial crisis reinforced the idea that "shifting" to macroprudential oversight would broaden the mandate of supervisors to the extent that a consideration of potential systemic risks and weaknesses was at the heart of the regulatory measures. Macroprudential measures are intended to make the financial system more resilient to crises and protect the real economy more effectively. Among the macroprudential measures provided in the new rules on banking supervision (Basel III), the capital conservation buffer (CCB) and countercyclical capital buffer (CCyB) are particularly important. While the CCB is intended to improve banks' general loss-absorbing capacity, the CCyB acts as an extension of the CCB and is primarily intended to counteract lending constraints in the event of a crisis. Regardless of how capital buffers are replenished (Berrospide & Edge, 2010; Repullo et al., 2010), owing to the full implementation of Basel III rules, banks' capital requirements have increased significantly. One of the potential implications is that doing business, particularly lending, has become more expensive for banks because of high equity costs.

There are two levers by which the banking system can improve its resilience to economic and financial shocks: increasing the levels of coverage of unexpected losses (regulatory capital) or, alternatively, reducing RWAs. While deleveraging under the first option strengthens a bank's capital soundness with positive effects on lending activity, when compliance with capital requirements is achieved with the simultaneous shrinkage of assets by a large majority of the banking system, the harm to the entire economy would be outweigh the benefits of increased capitalization (Hanson et al., 2011). Thus, how banks adjust their balance sheets in response to higher capital requirements is an empirical question of crucial importance to understand the real implications of such a regulatory measure.

Over the past decade, many empirical studies focused on the effects of binding capital requirements on bank lending. While stronger capital requirements lead to greater financial stability and less variability in lending activities over time, they can also reduce credit supply (Fraisse et al., 2020; Hyun & Rhee, 2011). Fraisse et al. (2020) find that a one-percentage-point increase in capital requirements reduced lending by 10% based on loans extended by French banks to French firms during 2008–2011. In a period characterized by serious contraction of the economy, a cut in lending of this magnitude becomes especially severe if it affects small businesses, whose operations are largely dependent on bank loans.

Another strand focuses on the impact of capital requirements on bank risk-taking. Some empirical studies find that under certain conditions, capital requirements are effective in improving risk-taking incentives (Furlong & Keeley, 1989; Repullo, 2004; Rochet, 1992). Berger and Udell (1994) show that higher capital requirements lead to reduced lending to riskier borrowers, while Barth et al. (2004) find that complying with stricter capital regulations reduces nonperforming loans (NPLs). Mayordomo and Rodríguez-Moreno (2018) present compelling evidence challenging the notion that lower capital requirements always lead to increased risk taking. Their findings suggest that relaxed capital requirements lead to more prudent behavior, with credit flowing predominantly to medium-sized firms, which are typically considered less risky than micro and small firms. In contrast to the aforementioned work, Blum (1999) argued that greater regulatory constraints may lead to greater risk-taking by banks while Calem and Rob (1999) added that greater risk appetite is related to bank's starting capital strength and the stringency of the capital rules they must meet. As suggested in Behn et al. (2015) and Fraisse et al. (2020), writing respectively about Germany and France, the stricter constraints imposed on banking capital levels have made lending much more sensitive to capital requirements. As it is generally recognized that MSMEs are, on average, riskier than large firms, they require banks to absorb more capital. Consequently, when the probability of default (PD) increases during economic downturns, lending to MSMEs becomes more hazardous and expensive for banks (Bangia et al., 2002). Moreover, credit access conditions for MSMEs worsen in the presence of institutional vacuums that fuel corruption and indirectly affect economic development through the provision of external credit (Wellalage et al., 2019). According to this interpretation, financial institutions reduce lending to MSMEs because they are considered a high-risk category, especially in environments characterized by ineffective legal contract enforcement and weak regulations. Corruption increases the cost of loans for MSMEs because it reduces their profitability and thus their ability to access credit. This complicates the way companies access external financing and makes it more difficult to enter into enforceable contracts with suppliers because of moral hazards and adverse selection problems. Banks tend to reduce their exposure to firms in this segment to meet the regulatory thresholds imposed on capital requirements.

The issue that we are interested in addressing in this work concerns the capital relief that the application of the SF to existing and newly issued loans brings to banks, and its impact on firms considered to be constrained. The results of recent empirical work on the introduction of the SF and its impact on capital relief for loans to small businesses are not unique. The first analysis, conducted by the European Banking Authority (2016), shows that the introduction of SF did not improve MSMEs' access to financing compared to large companies. In contrast, a study by the European Banking Federation did not completely reject the effectiveness of SF and encouraged further research. Dietsch et al. (2016) find that SF works both in the case of internal rating-based systems and, even more, in banks using the standard approach. Vozzella and Gabbi (2020) show that although the SF seems to assist MSME's credit access, there are significant differences with RWAs in terms of the regulatory regime and size of companies. This result depends on two factors: empirical asset correlation values are much lower than regulatory values, and the inverse relationship between asset correlation and risk embodied in the supervisory formula does not hold. Mayordomo and Rodríguez-Moreno (2018) show that SF alleviates credit rationing for medium-sized firms eligible for SF but not for micro and small firms.

Our study focuses on Italy, which, due to the weight of MSMEs, allows us to better understand whether size is a discriminating factor in classifying a firm as constrained and whether the introduction of the SF improves the likelihood that MSMEs have access to credit. Our findings suggest that with the current regulatory design, even after the introduction of the SF, MSMEs remain credit-constrained compared to large firms. In this context, where MSMEs play an important role in the economy and their main source of financing is bank credit, the risk-sensitive nature of capital requirements amplifies the cycle through the lending channel, making MSMEs even more vulnerable. Maintaining the stability of bank lending is important in economies where access to capital markets for MSMEs is difficult, and bank loans account for a significant part of the financial market.

3 | DATA AND METHODOLOGY

This study assesses the impact of a policy measure aimed at improving access to credit for micro and small enterprises. The analysis is based on data collected from Italian firms, which are ideal observatories due to the characteristics of the industrial system. In this section we describe the data used (Section 3.1), how we construct a proxy variable for credit rationing (Section 3.2) and the methodology used to measure the impact of policy measures such as SFs (Section 3.3).

3.1 | Sample

Previous empirical studies examining firms' access to finance have relied on annual data from the Survey on Access to Finance and Enterprises (SAFE),[2] a joint project of the European Commission and European Central Bank (ECB). Notable examples include the works of Casey and O'Toole (2014) and Ferrando et al. (2017). Unlike former contributions, we use the information on the firms' balance sheets and profit and loss accounts from Aida Bureau van Dijk's Amadeus Financial database to estimate the impact of MSME SF. Our data analysis is conducted at the firm level and considers the heterogeneity among firms and specific firm characteristics (such as size, financial health, and profitability) that cannot be evaluated when analyzing macroaggregated data. We developed a well-defined procedure to prepare and clean the data obtained from the database. Since the hypothesis that a 0 value often corresponds to a missing value is well-founded in the empirical literature on data analysis, we considered only variables with positive values. Moreover, we eliminate the outlier values of some financial ratios to better classify constrained and unconstrained companies. Values below the first percentile and above the ninth percentile were discarded. Finally, only firms with at least two consecutive balance sheet years were considered when computing the growth rates of all interest variables. As a result of this cleaning procedure, our final sample included approximately 450,000 firms and 1,642,490 observations. The panel is unbalanced, and the observation period runs from 2007 to 2017; therefore, it covers both the pre-SF (2007–2013) and post-SF (2014–2017).

Because information on the number of employees is not always available or sufficiently reliable, firms cannot be classified according to the criteria set out in Recommendation 2003/361/EC of the European Commission. Since we want to test the impact of SF on smaller firms, we use turnover as a parameter for classifying firms by size. Consequently, we classified all firms whose turnover did not exceed €50 million as MSMEs, whereas all others were considered large firms. To isolate the impact of SF on MSMEs, the latter is excluded from the basic analysis and constitutes our control group. We are aware that this classification procedure does not exclude the possibility that some large companies in the control group may be eligible for SF or that the treatment group may be contaminated by companies with a low level of turnover but a large company structure. However, an analysis based on cross-sectional time series data over a sufficiently long-time horizon should at least partially correct this possible bias.

Italy's industrial structure is largely characterized by small and very small firms, and the credit market is strongly segmented. According to the Annual Report on European Firms, MSMEs in Italy represent 79% of jobs in nonfinancial productive sectors (against an EU average of 67%) and 68% of added value (EU average of 57%). The incidence of microfirms in MSMEs is the highest in Europe (about 90%), and access to capital markets outside banking channels is far from the level of other major European countries. Moreover, the economic and financial structures are extremely heterogeneous among MSMEs. Therefore, in the second step of our analysis, we split our sample of MSMEs into micro-, small-, and medium-sized firms. The first are those with a turnover of up to 2 million, whereas small firms are classified as those with a turnover of between 2 and 10 million. The medium category consists of the remaining MSMEs. Table 1 shows an image of each sample. The variables used in the empirical analysis and their definition are presented in Table A1.

3.2 | How we define the dependent variable

Identifying a firm as constrained or unconstrained is difficult, especially when one cannot distinguish between demand and supply side factors. Mayordomo and Rodríguez-Moreno (2018), by using SAFE data, considered as constrained a firm that had received less than 75% of the amount requested for each loan or credit line. By contrast, unconstrained firms were those that had applied for a loan or credit line and received more than 75% of the amount requested. Firms that did not apply for loans and those that were rejected because they were considered risky were excluded. This is because these decisions depend on demand conditions, making it difficult to determine whether SFs influence a bank's decision to lend. This approach has the advantage of identifying a well-defined threshold; however, it could simultaneously be affected by a firm's behavioral biases.

Our approach is aimed at addressing this issue and represents a novelty due to the use of firms' balance sheet items to classify firms as credit-constrained or not. Using balance sheet data allows us to take a snapshot of a firm's economic and financial situation and classify it inductively as constrained or not constrained, eliminating the bias that could derive from the firm's perception of feeling rationed. One could criticize this by arguing that financial performance reflects the ability to conduct business and be efficient even in the presence of a credit crunch. Therefore, a firm can be constrained and maintain a balanced financial structure. For example, it could happen when it uses its bargaining power to substitute bank credit for trade credit. The role of trade credit as a financing resource for firms has been debated in economic literature. According to the substitution hypothesis, firms rely more heavily on trade credit when the difficulty of obtaining loans from banks increases

TABLE 1 Distribution of our sample by firm size.

	Number of observations	In percent
Size		
Large	17,294	1.05
Medium	145,951	8.89
Small	394,930	24.04
Micro	1,084,315	66.02
Total	1,642,490	100.00

Note: The number of observations and percentage weight of firms in our sample, split by size. The reference period was 2007–2017.

Source: Authors' elaboration on Aida Bureau Van Dijk database.

(Huang et al., 2011; Love et al., 2007; Nilsen, 2002; Petersen & Rajan, 1997). In contrast, another strand of the literature suggests a complementary relationship between trade and bank credit (Agostino & Trivieri, 2014; Biais & Gollier, 1997; Burkart & Ellingsen, 2004). Many empirical studies have focused on how the relationship between bank credit and trade credit affects a company's liquidity constraints (Coricelli & Frigerio, 2019; Fisman and Love, 2013; Love et al., 2007). Based on this awareness, we have decided to use, along with others, the net trade credit to sales ratio (NTCS) as a crucial variable for determining the status of "rationed firm." The NTCS is the ratio of trade credit (receivables minus payables) to sales. Multiplying by 360, the ratio is expressed in days and can be used as a duration indicator. Negative (positive) net trade credit values identify firms that are net borrowers (lenders) of trade credit. A sharp increase in net trade credit squeezes a firm's liquidity. If this is accompanied by a decrease in the share of bank debt in overall debt, a decline in the growth rate of turnover, and a worsening of creditworthiness, a company can be classified as constrained.

The conditions that must be satisfied for a company to be considered constrained are as follows (Equation 1):

$$\begin{cases} \frac{\mathrm{BD}_{i,t}}{\mathrm{TD}_{i,t}} < \frac{\mathrm{BD}_{i,t-1}}{\mathrm{TD}_{i,t-1}} \quad \text{and} \quad \mathrm{NTCS}_{i,t} > \mathrm{NTCS}_{i,t-1} \\ \mathrm{OR} \\ \frac{\mathrm{BD}_{i,t}}{\mathrm{TD}_{i,t}} < \frac{\mathrm{BD}_{i,t-1}}{\mathrm{TD}_{i,t-1}} \quad \text{and} \quad \mathrm{NTCS}_{i,t} \leq \mathrm{NTCS}_{i,t-1} \quad \text{and} \quad \mathrm{Score}_{i,t} < \mathrm{Score}_{i,t-1} \\ \mathrm{OR} \\ \frac{\mathrm{BD}_{i,t}}{\mathrm{TD}_{i,t}} < \frac{\mathrm{BD}_{i,t-1}}{\mathrm{TD}_{i,t-1}} \quad \text{and} \quad \mathrm{NTCS}_{i,t} \leq \mathrm{NTCS}_{i,t-1} \quad \text{and} \quad \mathrm{Score}_{i,t} \geq \mathrm{Score}_{i,t-1} \quad \text{and} \quad \mathrm{SGR}_{i,t} \end{cases} . \tag{1}$$

where BD to $\mathrm{TD}_{i,t}$ is the ratio of bank debt to the total debt of the i-th firm at time t; $\mathrm{NTCS}_{i,t}$ is the net trade credit (receivables – payables) to the sales of the i-th firm at time t; $\mathrm{Score}_{i,t}$ is the i-th firm creditworthiness at time t; $\mathrm{SGR}_{i,t}$ is the sales growth rate of the i-th firm at time t.

Based on these conditions, firms are associated with a value of 1 when they are financially rationed and 0 otherwise. Table 2 shows the distribution by sample size between constrained and nonconstrained firms. Interestingly, the percentage of firms classified as constrained is

TABLE 2 Distribution of the sample by "status" and size.

	Large	Medium	Small	Micro	Total
Firms (observations)	17,294	145,951	394,930	1,084,315	1,642,490
Not constrained	12.900	112,022	295,118	745,246	1,165,286
Percentage by size	1.11	9.61	25.33	63.95	100.00
Percentage by status	74.59	76.75	74.73	68.73	70.95
Constrained	4394	33,929	99,812	339,069	477,204
Percentage by size	0.92	7.11	20.92	71.05	100.00
Percentage by status	25.41	23.25	25.27	31.27	29.05

Note: The percentage distribution of the firms in our sample between constrained and not constrained and, within this classification, the percentage weights of the different size classes. The reference period was 2007–2017.

Source: Authors' elaboration on Aida Bureau Van Dijk database.

much higher among microfirms (more than 31%), whereas it is very similar among other size classes. Therefore, our data support the hypothesis that credit rationing is much more pronounced in small and very small firms because they are perceived as more vulnerable to systematic risk factors and, therefore, riskier than large firms.

3.3 | Difference in differences estimator and control variables

DiD estimation is a methodology mainly used in microeconometrics to estimate the effect of a "treatment" (e.g., the introduction of a policy measure) on a group of subjects ("treated"), relative to a second group of subjects not exposed to the treatment ("control" group). The two groups are observed in two periods, one before and one after treatment. The frequent use of the DiD estimator in research stems from the fact that it circumvents many endogeneity issues that typically arise when comparing heterogeneous individuals. The hypothesis underlying the DiD estimator requires that the treated and control groups follow a similar trend in the absence of treatment ("parallel trend hypothesis"). Therefore, in our case, MSMEs (treated group) and large firms (control group) should show a common trend in our variable of interest, that is, being constrained or not constrained. We conducted a dynamic test to test this hypothesis. The results in Table 9 show that there is no significant difference in the trends of our dependent variable between the treatment and control firms before the introduction of SF; therefore, the critical assumption of parallel trends underlying our DiD design is satisfied. In addition, the dynamic test revealed that the probability of being tied showed no significant change in MSME for up to 4 years after the introduction of the SF.

As the ability to access credit reflects the number of loans that the credit system makes available to companies, Figure 1 shows the evolution of the flow of new loans to nonfinancial corporations (NFCs) between 2007 and 2017.

The dotted line represents loans to MSMEs and refers to loans of up to EUR 1 million, whereas the solid line represents large corporations and includes only the flow of new loans above EUR 1 million. As the amounts were significantly different, we normalized the values to January 1, 2014, the year in which the SF came into effect (dashed vertical lines). Large firms and MSMEs were characterized by a drastic downward trend in the early years of the crisis. The reduction in the flow of new loans is also marked for large firms in the years immediately following and up to the first half of 2014, while the granting of new loans to MSMEs seemed to have become already stabilize in the second half of 2010. Although the graph shows a marked difference in the overall level of new loans, large firms and MSMEs show homogeneous trends before and after the introduction of SF.

Unlike previous studies, our analysis was based on pooled cross-sectional time-series data. This allows us to reduce the impact of the temporary and unconventional monetary policy measures adopted by the ECB in response to the financial crisis on our estimates, such as additional longer-term refinancing operations and other asset purchase programs and capture the intrinsic characteristics of access to credit for micro-, small-, and medium-sized firms. Econometric estimates to test whether and how the application of SF led to easier access to credit for MSMEs than for large firms were carried out using a logit model. We then estimate the following DiDs regression specification (Equation 2):

$$\begin{aligned}\text{Constrained}\quad \text{firm} = \alpha + \beta_1 \text{MSME}_i + \beta_2 \text{SF}_t + \beta_3 \text{MSME}_i \times \text{SF}_t + \tau \text{FIRM}F_{it} \\ + \gamma \text{REGION}F_{jt} + \eta_j + \eta_t + \eta_s + \epsilon_{ijst}.\end{aligned} \tag{2}$$

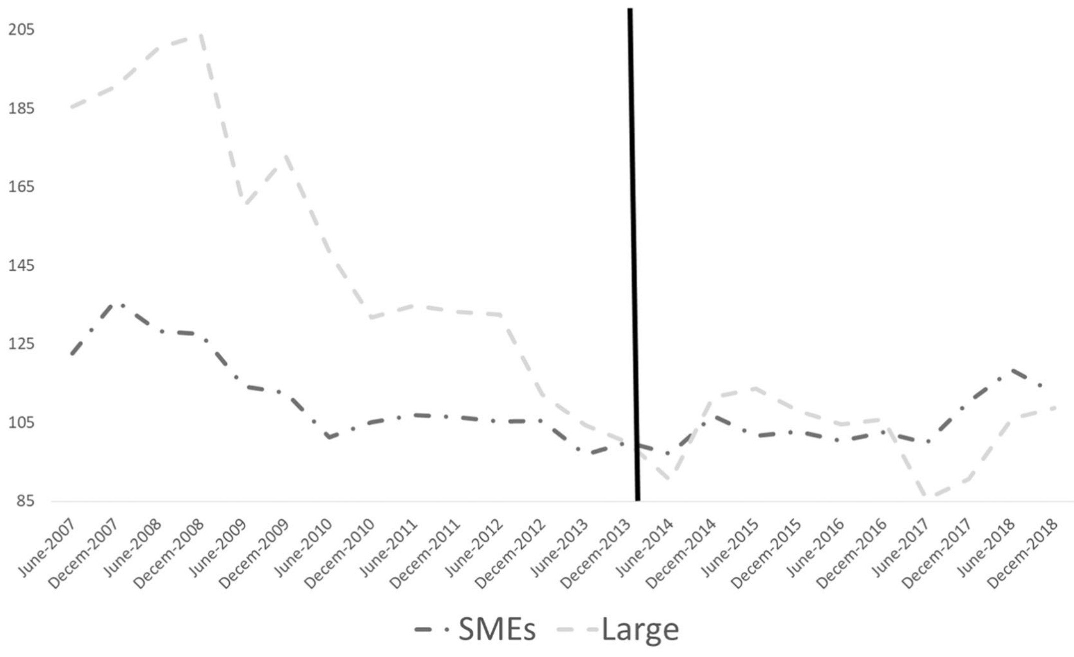

FIGURE 1 Flow of new lending to MSMEs and large firms. The graph depicts the 6-month moving average of the flow of new lending to nonfinancial corporations before and after the introduction of the SF in January 2014 by size of firm. Loans of less than 1 million euro are considered as loans to MSMEs whereas those larger than 1 million are considered as loans to large firms. The two series are standardized to one at January 2014. MSME, micro, small, and medium enterprises; SF, supporting factor; SME, small and medium enterprises. *Source*: Authors' elaboration on the Bank of Italy database.

Our dependent variable (constrained firm) is a dummy that takes the value of 1 when, based on the filters we set, a firm appears financially constrained, and 0 otherwise. MSME is a dummy that takes the value of 1 for MSME and 0 otherwise. SF is a dummy variable that equals 1 from the year the SF took effect and 0 in previous years. MSME × SF represents the interaction between the two. FIRMF refers to firm characteristics, specifically age, and profitability. To intercept environmental and macroeconomic factors, we include the variables REGIONF, which includes the real growth rate of regional GDP (RR GdP GR), the regional NPLs rate, and the ratio of loans to households (HHs) and NFCs to regional GDP (loans to NFCs HH to GdP). Finally, we use geography (η_j), years (η_t) and sectors (η_s) in the analysis as additional control variables to absorb shocks that affect all firms in a given region, year, or sector. Table 3 reports Person's correlation coefficients for the variables used in our empirical analysis,[3] while in the appendix we present the main details on the structure of the sample and on the control variables.

4 | EMPIRICAL RESULTS

In this section, we test the predictions of our models using full-sample information. In the baseline analysis (Table 4), we regress our dependent variable on a dummy that equals one when a firm is classified as an MSME and zero for large firms. In this context, we also

TABLE 3 Pearson's correlation coefficients.

	Constrained	D.Micro	D.Small	D.Medium	D.After SF	EC	RC	Age	RR GdP GR	Loans to NFCs HH to GdP	NPLs rate	Profitability
Constrained	1											
D.Micro	.068***	1										
D.Small	−.047***	−.784***	1									
D.Medium	−.040***	−.435***	−.176***	1								
D.After SF	−.011***	−.015***	.005***	.015***	1							
EC	.026***	.066***	−.244***	.012***	−.026***	1						
RC	−.078***	−.673***	.310***	.576***	.058***	−.214***	1					
Age	−.022***	−.256***	.148***	.183***	−.107***	−.035***	.281***	1				
RR GdP GR	−.033***	−.040***	.021***	.028***	−.008***	−.003***	.045***	−.008***	1			
Loans to NFCs HH to GdP	−.010***	−.046***	.021***	.035***	.103***	.014***	.040***	.103***	.014***	1		
NPLs rate	.036***	.074***	−.043***	−.049***	−.067***	−.001	−.068***	−.067***	−.520***	−.105***	1	
Profitability	.001	.001	−.001	.000	.001	−.004***	.004***	.000	−.001	−.001	.001	1

Note: The Pearson's correlation coefficients. Constrained is a dummy variable that takes the value of one when a firm is financially rationed and zero otherwise. D.Micro is a dummy variable that takes the value of 1 when the firm falls within the microsize class and 0 otherwise. D.Small is a dummy variable that takes the value of 1 when a firm falls within the small-size class and 0 otherwise. D.Medium is a dummy variable that takes the value of 1 when the firm falls within the medium-sized class, and 0 otherwise. D.After SF is a dummy variable that equals 1 after SF comes into force and 0 otherwise. Age measures the time between the initial creation of a firm and the present (in years). RR GdP GR is the real growth rate of the regional gross domestic product. Loans to NFCs and HHs to GdP refer to loans to HH and NFC as a proportion of the GDP. NPLs rate is the ratio of the annual flow of adjusted NPLs to the stock of performing loans in the previous year (NPLs ratio). Profitability refers to the earnings before interest and taxes.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

Abbreviations: EC, empirical asset correlation; GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan; RC, regulatory asset correlation; SF, supporting factor.

TABLE 4 The MSME credit conditions after the introduction of the supporting factor.

	Model 1	Model 2	Model 3	Model 4
D.MSME	−0.0189	−0.0189	−0.0273	−0.0354
	[0.0228]	[0.0228]	[0.0358]	[0.0357]
D.After SF		0.0668***	0.0376	0.0288
		[0.0144]	[0.064]	[0.0671]
D.MSME × D.After SF			0.0295	0.0195
			[0.059]	[0.0647]
Age				−0.0024***
				[0.000345]
Profitability				0.000185
				[0.000146]
RR GdP GR				−1.004***
				[0.28]
NPLs rate				0.0120**
				[0.00539]
Loans to NFCs HH to GdP				−0.000832
				[0.00121]
Number of obs.	1,642,490	1,642,490	1,642,490	1,550,707
Regional effects	Yes	Yes	Yes	Yes
χ^2	2.20E + 07	2.20E + 07	3.60E + 07	9.90E + 06
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Time effects	Yes	Yes	Yes	Yes
χ^2	17,117.07	11,713.87	11,684.54	1317.33
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Sector effects	Yes	Yes	Yes	Yes
χ^2	92,211.13	687.00	685.24	863.6
Prob > χ^2	0.0000	0.0000	0.0000	0.0000

Note: The logit estimates of Equation (2) for the period 2007–2017. The dependent variable is a dummy that equals one when firm is classified as constrained based on conditions (1) and zero otherwise. Our variables of interest are: D.MSME, D.After SF, and D.MSME × D.After SF. D.MSME takes value 1 when firm is belonging to the MSME segment and 0 otherwise. D.After SF is a dummy that equals one after that SF came into force and zero otherwise. D.MSME × D.After SF is their interaction. The set of control variables refers both to firm characteristics (age and profitability) and geographic characteristics (RR GdP GR, NPLs rate, loans to NFCs and HH to GdP).

Standard errors are clustered at the regional level and are reported in brackets.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively. The table also reports the statistics of the Wald test (χ^2 and Prob).

Abbreviations: GDP, gross domestic product; HH, household; MSME, micro, small, and medium enterprises; NFC, nonfinancial corporation; NPL, nonperforming loan; SF, supporting factor.

introduce fixed effects to control for unobserved heterogeneity at the regional, time, and sector levels.

In Model 1 in Table 4, the coefficient of the dummy variable referring to MSMEs is not statistically significant, and the fixed effects capture all variability due to heterogeneity in regional, sectoral, and temporal factors. Interestingly, in Model 2, although the MSME dummy continues to be nonsignificant, the coefficient of the D.After SF variable, statistically significant at the 1%, means that the probability of being credit-constrained has increased overall in the years following the introduction of the SF. The *p*-value, referring to fixed effects, confirms the relevance of these factors to Italy's credit access conditions.

This hypothesis is confirmed by the results of Models 3 and 4, in which all the variables of major interest are nonsignificant. Specifically, the interaction between the firm size dummy and the dummy referring to the years after the introduction of SF suggests that, overall, the condition of MSMEs remains unchanged relative to that of large firms. More importantly, the results of the fixed effects, particularly those related to geographic heterogeneity, confirm their crucial role in MSMEs' access to credit in Italy. Finally, all control variables related to firm characteristics (age and profitability) and geographic characteristics (RR GdP GR, NPLs rate, and loans to NFCs HH to GdP) confirm the expected sign; apart from profitability and the characteristics of the banking sector (loans to NFCs and HH to GDP), all others display a statistical significance at the 1% level. Therefore, our findings on business profitability suggest that the cause of rationing depends mainly on structural and systemic factors and not idiosyncratic factors. On the other hand, an increase in the regional GDP growth rate and a reduction in the NPLs rate have a sizeable impact on the likelihood of being constrained. Notably, the inclusion of control variables affects neither the sign nor magnitude of the estimated coefficients of the main variables of interest. This finding suggests that the credit-SF has different effects depending on firm size.

Our baseline results suggest that the introduction of SF does not appear to have facilitated access to credit for MSMEs as a whole relative to large firms, and the lower the likelihood of being credit-constrained, the more generalized the country's growth. MSMEs exhibit remarkable heterogeneity in various aspects such as size, risk, and profitability, which consequently affects their access to credit. The European Banking Authority (2016) highlights that the risk profiles of MSMEs and large firms follow a cyclical pattern. During economic downturns, all firms experience deteriorating indicators, with small firms facing more severe challenges than medium and large firms do. Moreover, medium-sized firms tended to perform better. Despite the heterogeneity of the MSME group, banks can benefit from financing both micro/small and medium-sized enterprises through special financing. Given the differences between firms based on size, it is reasonable to assume that banks may treat micro/small firms differently than medium firms, opting to take advantage of the lower cost of capital associated with SF when lending to medium firms. Therefore, it is important to distinguish between different types of MSMEs.

In light of these considerations, we divided the dummy for MSMEs into three dummy variables for micro-, small-, and medium-sized firms that take the value 1 when they are in the reference size class and 0 otherwise, and made each of the three variables interact with the dummy related to the SF (D.After SF) (Equation 3):

$$\begin{aligned}\text{Constrained}\quad \text{firms} = {} & \alpha + \beta_1 \text{Micro}_i + \beta_2 \text{Small}_i + \beta_3 \text{Medium}_i + \beta_4 \text{Micro}_i \times \text{SF}_t + \beta_5 \\ & \text{Small}_i \times \text{SF}_t + \beta_6 \text{Medium}_i \times \text{SF}_t + \beta_7 \text{SF}_t + \tau \text{Firm}F_{it} \\ & + \gamma \text{Region}F_{jt} + \eta_j + \eta_t + \eta_s + \epsilon_{ijst}.\end{aligned} \tag{3}$$

The results are presented in Table 5. The patterns show significant differences within the MSME segments. The estimates from Model 1 indicate that microfirms appear to be the only ones that are credit-constrained (positive and statistically significant coefficient). Specifically, we find that the probability of micro-firms not being able to access credit is approximately 8% higher than that of other firms. In addition, the probability of being credit-constrained decreases as firm size increases.

The results do not change when we introduce the dummy variable related to SF (Model 2), whose positive and statistically highly significant coefficient indicates that even in the years following its introduction, the probability of being credit-constrained increases overall. This result is consistent with the fact that microfirms are considered riskier than small- and medium-sized firms, and therefore, are not treated by banks in the same way. Interestingly, the statistically insignificant coefficients of the interaction between the after SF dummy variable and the dummies for the size classes in Models 3 and 4 confirm that credit access conditions within the MSME segment do not change with SF. In contrast, the results for micro firms in specifications 3 and 4 seem to suggest that their condition is not "absolute" but is highly conditioned by regional, sectorial, and temporal factors as evidenced by the significance levels of the fixed effects and control variables, particularly those that are related to regional characteristics. Our findings indicate that, at least in Italy, SF has not had the desired effects and has not been able to compensate for the impacts of geographic differences, sector characteristics, or the production cycle on credit access opportunities. Overall, the results in Table 5 support the hypothesis that banks are more likely to use capital relief from SF implementation to lend to medium-sized firms but not to the entire MSME spectrum.

Although the riskiness of MSMEs and large firms shows a cyclical pattern (European Banking Authority, 2016), micro-, small-, and medium-sized firms behave very heterogeneously among themselves and overall; during recessionary periods, they generally suffer much more than large firms and are relatively worse off. Consequently, access to credit became tighter. This problem becomes even more significant in the presence of loan portfolios that are highly concentrated in a few size classes and in sectors that are highly dependent on the economic cycle. This is the case for local and small- to medium-sized banks.

The probability of being constrained may depend significantly on the degree of correlation between companies and/or sectors. Moreover, a company's risk profile depends not only on its specific characteristics, but also on its degree of correlation with other borrowers and its exposure to economic fluctuations (capital correlation). The latter explains the extreme values of a loan portfolio and plays a crucial role in calculating unexpected losses and the resulting capital absorbed.

MSMEs are characterized by a higher PD than large firms, and this tendency strengthens during recessionary periods, whereas systematic risk factors increase with firm size. The combined effect of these factors and their impact on banks' capital requirements lead to a credit crunch for MSMEs. To mitigate this procyclical attitude of the banking systems involved in capital requirements architecture, the asset correlation parameter established by the Basel framework is invariant to business cycles, decreases with borrowers' PD, and increases with borrowers' assets. However, many empirical studies (Dietsch & Petey, 2004; Gabbi & Vozzella, 2013; Lopez, 2004) have shown an empirical relationship between asset correlation and PD that differs significantly from that assumed by the regulatory formula. Vozzella and Gabbi (2017) found a positive relationship between PD and asset correlation in Italy, and the values of the latter fell within a much smaller range than the regulatory ones. In addition, the authors showed that the relationship between asset correlation and size is not linear and changes with the economic cycle (Vozzella & Gabbi, 2022).

TABLE 5 The heterogeneous firm responses after the introduction of the supporting factor.

	Model 1	Model 2	Model 3	Model 4
D.Micro	0.0695***	0.0695***	0.0607	0.0608
	[0.0256]	[0.0256]	[0.0377]	[0.0377]
D.Small	−0.107***	−0.107***	−0.113***	−0.107***
	[0.02]	[0.02]	[0.0325]	[0.0335]
D.Medium	−0.173***	−0.173***	−0.177***	−0.171***
	[0.0165]	[0.0165]	[0.029]	[0.0313]
D.After SF		0.0588***	0.0322	0.0321
		[0.0146]	[0.0633]	[0.0664]
D.Micro × D.After SF			0.0307	0.0229
			[0.0577]	[0.0631]
D.Small × D.After SF			0.0203	0.0122
			[0.0599]	[0.0653]
D.Medium × D.After SF			0.0148	0.0062
			[0.0593]	[0.0648]
Age				−0.000764***
				[0.000243]
Profitability				0.000194
				[0.000145]
RR GdP GR				−1.015***
				[0.284]
NPLs rate				0.0121**
				[0.00544]
Loans to NFCs HH to GdP				−0.000851
				[0.00122]
Number of obs.	1,642,490	1,642,490	1,642,490	1,550,707
Regional effects	Yes	Yes	Yes	Yes
χ^2	4.30E + 06	4.30E + 06	3.60E + 06	1.20E + 08
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Time effects	Yes	Yes	Yes	Yes
χ^2	14,628.04	11,475.59	11,045.02	1265.18
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Sector effects	Yes	Yes	Yes	Yes

(Continues)

TABLE 5 (Continued)

	Model 1	Model 2	Model 3	Model 4
χ^2	1037.27	1037.27	1027.38	1020.89
Prob > χ^2	0.0000	0.0000	0.0000	0.0000

Note: This table reports the logit estimates of Equation (3) for the period 2007–2017. The dependent variable is a dummy that equals one when firm is classified as constrained based on conditions (1) and zero otherwise. Differently with the regressions in Table 4, here we have partitioned the MSME segment into the different size classes that it represents. Now, our variables of interest are: D.Micro, D.Small, and D.Medium that takes value 1 when firm falls within the micro, small, and medium size, respectively and 0 otherwise, D.After SF, that is equal to 1 after the SF came into force and 0 otherwise, and the interaction between each of the dummies for firm size classes and D.After SF. The set of control variables refers both to firm characteristics (age and profitability) and geographic characteristics (RR GdP GR, NPLs rate, Loans to NFCs and HH to GdP).

Standard errors are clustered at the regional level and are reported in brackets.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively. Table also reports the statistics of the Wald test (χ^2 and Prob).

Abbreviations: GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan; SF, supporting factor.

Although our work is not aimed at testing the robustness of the assumptions regarding the asset correlation parameters underlying the regulatory formula, in the models presented in Tables 6 and 8, we regress our dependent variable on both the asset correlation values derived from the application of the regulatory formula (RC) and those derived from Vozzella and Gabbi's (2020) empirical analysis of Italy (EC) (Equation 4). Specifically:

$$\begin{aligned}\text{Constrained}\quad \text{firms} = {} & \alpha + \beta_1 \text{Micro}_i + \beta_2 \text{Small}_i + \beta_3 \text{Medium}_i + \beta_4 \text{Micro}_i \times \text{SF}_t + \beta_5 \\ & \text{Small}_i \times \text{SF}_t + \beta_6 \text{Medium}_i \times \text{SF}_t + \beta_7 \text{SF}_t + \beta_8 \text{AC}_t + \tau \text{Firm}F_{it} \\ & + \gamma \text{Region}F_{jt} + \eta_j + \eta_t + \eta_s + \epsilon_{ijst}.\end{aligned} \tag{4}$$

This part of the analysis represents another element of originality in our contribution to the financial literature on credit-constrained firms. We aim to understand whether decisions about possible credit rationing depend not only on firms' characteristics and the sectors and geographical areas in which they operate but also on the elements of the banking portfolio.

The regressions in Table 6 introduce among the independent variables the regulatory asset correlation parameter[4] (RC). Under the advanced internal ratings-based approach, the asset correlation plays an important role in calculating banks' capital requirements. Broadly, it is used to quantify the magnitude and direction of asset value fluctuations in response to economic risks. It plays a crucial role in the assessment of extreme values within a loan portfolio and thus influences the calculation of unexpected losses and the corresponding capital absorption. To address the concerns raised by national supervisors regarding the calibration of credit risk measures for MSMEs, two key assumptions are introduced. First, we assumed a positive relationship between asset correlation and firm size. The assumption is that lower asset correlations lead to portfolio diversification, thereby reducing overall risk. Banking regulations establish an inverse relationship between asset correlation and a firm's PD to mitigate the impact of business cycles on RWAs. This approach allows banks to apply capital haircuts to loans to MSMEs as they are more vulnerable during economic transitions due to their higher PD. The prudential principle aims to reduce the cyclical sensitivity of RWA, enhancing the stability of financial institutions. This calibration is particularly beneficial for firms with a

TABLE 6 The heterogeneous firm responses after the introduction of the supporting factor.

	Model 1	Model 2	Model 3	Model 4
D.Micro	−0.318***	−0.318***	−0.327***	−0.314***
	[0.0298]	[0.0298]	[0.038]	[0.0391]
D.Small	−0.344***	−0.344***	−0.351***	−0.340***
	[0.0234]	[0.0234]	[0.032]	[0.0337]
D.Medium	−0.216***	−0.216***	−0.221***	−0.215***
	[0.0164]	[0.0164]	[0.0283]	[0.0307]
D.After SF		0.0842***	0.0545	0.0574
		[0.0152]	[0.0636]	[0.0668]
D.Micro × D.After SF			0.0321	0.0264
			[0.0571]	[0.0626]
D.Small × D.After SF			0.0269	0.0198
			[0.0591]	[0.0644]
D.Medium × D.After SF			0.0207	0.0124
			[0.0585]	[0.0639]
Age				0.000299
				[0.000247]
Profitability				0.000298
				[0.000213]
RR GdP GR				−1.016***
				[0.286]
NPLs rate				0.0121**
				[0.0053]
Loans to NFCs HH to GdP				−0.000986
				[0.00118]
RC	−4.343***	−4.343***	−4.342***	−4.311***
	[0.247]	[0.247]	[0.247]	[0.254]
Number of obs.	1,642,490	1,642,490	1,642,490	1,550,707
Regional effects	Yes	Yes	Yes	Yes
χ^2	8.50E + 06	8.50E + 06	1.60E + 07	5.20E + 07
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Time effects	Yes	Yes	Yes	Yes
χ^2	14,683.26	11,769	11,293.31	1529.49
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Sector effects	Yes	Yes	Yes	Yes

(Continues)

TABLE 6 (Continued)

	Model 1	Model 2	Model 3	Model 4
χ^2	1425.65	1425.65	1421.75	965.35
Prob > χ^2	0.0000	0.0000	0.0000	0.0000

Note: The role of banking portfolio with the regulatory asset correlation values (RC).

The novelty of Table 6 is the introduction of independent variables of the regulatory asset correlation values, as in Vozzella and Gabbi (2020). This table reports the logit estimates of Equation (4) for the period 2007–2017. The dependent variable is a dummy that equals one when the firm is classified as constrained based on condition (1) and zero otherwise. Our variables of interest are D.Micro, D.Small, and D.Medium, which take the value of 1 when a firm falls within the micro, small, and medium sizes, respectively, and 0 otherwise; D.After SF, which is equal to 1 after SF came into force and 0 otherwise; and the interaction between each of the dummies for firm size classes and D.After SF. Finally, we add the regulatory asset correlation (RC) variable to estimate the impact of portfolio concentration on MSMEs' access to credit. The set of control variables refers to firm characteristics (age and profitability) and geographical characteristics (RR GdP GR, NPLs rate, loans to NFCs and HH to GdP).

Standard errors are clustered at the regional level and reported in parentheses.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively. The table also reports the Wald test (χ^2 and Prob).

Abbreviations: GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan; SF, supporting factor.

turnover of up to EUR 50 million and ensures a more balanced approach to capital requirements. The rationale is that MSMEs benefit from more diversified portfolios and are more sensitive to the business cycle than large firms; therefore, MSMEs suffer more when the economy moves from a growth phase to a recession phase because of their higher PDs. As asset correlation and PD are the key drivers for credit risk models, their proper calibration becomes crucial for the reliability of the overall scheme to address the cyclicality issue under Basel regulations. This is also because the metrics underlying the calculation of capital absorption (e.g., value-at-risk) are very sensitive to changes in these two parameters.

The coefficients of the explanatory variables are always negative and statistically significant at the 1% level in all the models when considering the asset correlation values derived by applying the regulatory formula (RC). The probability of being subject to credit restrictions decreases as the firm size decreases. Specifically, the coefficient of the dummy micro indicates that, on average, the probability of microfirms being credit constrained is reduced by approximately 30% relative to other firms, while in medium-sized firms, the reduction is approximately 20%. Our estimates remain essentially the same in all the regressions. More importantly, the negative and statistically significant sign of the RC coefficient suggests that an increase in the asset correlation value translates, overall, to less difficulty in accessing credit. However, since asset correlation increases as the PD decreases, and thus as creditworthiness improves, this benefit falls primarily on firms with the best rating grades. The positive and significant coefficient of the variable D.After SF in Model 2 supports this interpretation.

The result that is particularly relevant for our analysis relates to the interactions between firm size dummies and the D.After SF variable (Models 3 and 4). As we have already seen in all the models presented above, the coefficients are never statistically significant, regardless of the size class considered, confirming that SF has had no impact on alleviating the credit-constrained condition of MSMEs in Italy. Finally, all the control variables show the expected signs and significance levels. The significance of the fixed effects supports our hypothesis regarding the crucial role that geographical location and sectoral characteristics, as well as the business cycle phase, play in explaining the differences in MSMEs' access to credit. Overall, the regressions in Table 6 confirm that, in Italy, the introduction of SF did not produce the desired effects in relation to MSMEs' credit access conditions. Our evidence suggests that because banks benefit from SF regardless of whether they lend to micro-, small-, or medium-sized firms, they choose to lend primarily to those with greater credit strength because they receive the same capital relief and lower overall risk.

If the correlation coefficients between loans to micro and small enterprises are indeed higher than those for large enterprises, credit rationing for MSMEs would be rational. In reality, as shown in Table 7, the regulatory correlations, and even more so the empirical correlations observed for Italy by Vozzella and Gabbi (2020), result in a marginal diversification benefit from increased lending to MSMEs. As several empirical studies in the financial literature mentioned above have shown, the empirical values indicate that the inverse relationship between asset correlation and the risk underlying the regulatory formula for calculating banks' RWAs does not hold. Moreover, the empirical values are much lower than those suggested by the capital requirement regulations. Finally, asset correlation values are lower among micro-firms than among firms in other size classes, particularly large firms. Taken together, these findings suggest that, if the regulatory hypothesis does not hold, the procyclicality inherent in bank capital regulation is amplified rather than mitigated.

In the models presented in Table 8, we then replaced the asset correlation values derived by applying the regulatory formula (RC) with empirical asset correlation values (EC) taken from Vozzella and Gabbi (2020). The regression results presented in Table 8 are interesting for several reasons. First, in contrast with what we have seen in the models shown in Table 6,

TABLE 7 Regulatory asset correlations versus empirical assets correlations.

Risk classes	Large	Medium	Small	Micro
(a) Asset correlation based on Basel III formula (RC)				
A	0.234	0.228	0.186	0.153
B	0.225	0.223	0.185	0.145
C	0.218	0.211	0.171	0.134
D	0.184	0.170	0.131	0.105
E	0.145	0.122	0.087	0.069
F	0.120	0.120	0.084	0.031
(b) Empirical asset correlation (EC)				
A	0.054	0.016	0.014	0.020
B	0.136	0.025	0.020	0.021
C	0.042	0.023	0.016	0.018
D	0.087	0.026	0.024	0.026
E	0.239	0.038	0.022	0.034
F	0.214	0.104	0.059	0.067

Note: Panel (a) shows the asset correlation values (RC) calculated by applying the normative formula to calculate risk-weighted assets. Panel (b) presents the empirical asset correlation values estimated for Italy. The risk classes are ordered in ascending order, with letter A indicating the lowest probability of default and letter F indicating firms with the highest probability of default. All the data in this table were obtained from Vozzella and Gabbi (2020).

TABLE 8 The heterogeneous firm responses after the introduction of the supporting factor.

	Model 1	Model 2	Model 3	Model 4
D.Micro	0.698***	0.698***	0.695***	0.690***
	[0.0851]	[0.0851]	[0.0976]	[0.0975]
D.Small	0.558***	0.558***	0.557***	0.555***
	[0.0828]	[0.0828]	[0.0959]	[0.096]
D.Medium	0.453***	0.453***	0.453***	0.450***
	[0.0768]	[0.0768]	[0.0895]	[0.0907]
D.After SF		0.0668***	0.0598	0.0614
		[0.015]	[0.0695]	[0.0727]
D.Micro × D.After SF			0.00991	0.00223
			[0.063]	[0.0687]
D.Small × D.After SF			0.00183	−0.00646
			[0.0655]	[0.071]
D.Medium × D.After SF			−0.00137	−0.0103
			[0.0645]	[0.0701]
Age				−0.000438*
				[0.000228]
Profitability				0.000247
				[0.000165]
RR GdP GR				−1.021***
				[0.284]
NPLs rate				0.0121**
				[0.00542]
Loans to NFCs HH to GdP				−0.000869
				[0.00121]
EC	10.59***	10.59***	10.58***	10.50***
	[1.027]	[1.027]	[1.029]	[1.031]
Number of obs.	1,642,490	1,642,490	1,642,490	1,550,707
Regional effects	Yes	Yes	Yes	Yes
χ^2	2.30E + 09	2.30E + 09	1.20E + 07	3.40E + 07
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Time effects	Yes	Yes	Yes	Yes
χ^2	14,791.14	11,720.1	11,244.9	1361.38
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Sector effects	Yes	Yes	Yes	Yes

TABLE 8 (Continued)

	Model 1	Model 2	Model 3	Model 4
χ^2	1122.59	1122.59	1116.44	1880.15
Prob > χ^2	0.0000	0.0000	0.0000	0.0000

Note: The role of banking portfolio when empirical asset correlation values (EC) are considered.

The logit estimates of Equation (4) for the period 2007–2017. The dependent variable is a dummy that equals one when the firm is classified as constrained based on condition (1) and zero otherwise. Our variables of interest are D.Micro, D.Small, and D.Medium, which take the value of 1 when a firm falls within the micro, small, and medium sizes, respectively, and 0 otherwise; D.After SF, which is equal to 1 after SF came into force and 0 otherwise; and the interaction between each of the dummies for firm size classes and D.After SF. We add an empirical asset correlation regressor (EC) to estimate the impact of portfolio concentration on MSMEs' access to credit. The set of control variables refers to firm characteristics (age and profitability) and geographical characteristics (RR GdP GR, NPLs rate, loans to NFCs and HH to GdP).

Standard errors are clustered at the regional level and reported in parentheses.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively. The table also reports the Wald test (χ^2 and Prob).

Abbreviations: GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan; SF, supporting factor.

when we consider the empirical values (EC), the coefficients on dummies by size class show a positive and very significant sign in all the estimated models. Thus, MSMEs face greater difficulties accessing credit than large firms. Second, the probability of being credit-constrained decreases as firm size increases. The results hold, both in general (Model 1) and after the introduction of SF, as suggested by the positive and statistically significant coefficient of the D.After SF variable (Model 2). More importantly, contrary to the results in Table 6, the common risk factor coefficient (EC) is positive and highly statistically significant, indicating that the propensity to be constrained increases with the capital correlation. Specifically, in contrast to what is suggested by the negative sign of the coefficient RC variable, this result is consistent with portfolio management risk theory. As empirical values (EC) are positively correlated with risk, and MSMEs are generally perceived as riskier than larger firms, an increase in values affects the likelihood of being constrained. As seen in all the previous models, the introduction of SF had no effect on MSME access to credit. The interaction between the dummy for firm size class and that for SF (Models 3 and 4) shows a statistically nonsignificant coefficient regardless of firm size. The control variables relative to regional characteristics and firm longevity show the expected signs and are almost always statistically significant (Model 4). The statistical significance of the fixed effects confirms that regional and sectorial characteristics are key factors in Italian credit policies.

If the trend of our dependent variable (that is, the probability of being constrained) is already different between our treatment group (micro-, small-, and medium-sized firms, MSME) and our control group (i.e., large firms) before the introduction of the MSME SF, the critical assumption of parallel trends underlying our DiD design would also be violated. To investigate this issue, we follow the dynamic models used by Chen et al. (2018) and Fang et al. (2014) and examine the evolution of the probability of being tied in both MSMEs and large firms from year $t-4$ to $t+4$ of the introduction of the SF. Specifically, we replace D.After SF with a dummy variable representing each year in the [−4, +4] event window (e.g., Year 0 is the SF signing year, Year −1 is 1 year before the introduction of the SF, and Year 1 is 1 year after the SF signing year) and rerun Equation (2). Table 9 reports the results of dynamic tests

TABLE 9 Dynamic test.

Variables	Constrained/not constrained
Treat × Year −4	−0.116**
	(0.0393)
Treat × Year −3	0.123
	(0.0959)
Treat × Year −2	0.0430
	(0.0749)
Treat × Year −1	−0.00227
	(0.133)
Treat × Year 1	0.0648
	(0.0794)
Treat × Year 2	0.160
	(0.136)
Treat × Year 3	−0.000995
	(0.0976)
Treat × Year 4	0.0945
	(0.103)
Treat	−0.0469
	(0.0460)
Year −4	0.0832**
	(0.0403)
Year −3	−0.193*
	(0.106)
Year −2	−0.155**
	(0.0745)
Year −1	−0.136
	(0.143)
Year 1	−0.249***
	(0.0785)
Year 2	−0.368**
	(0.152)
Year 3	−0.145
	(0.0964)
Year 4	−0.314***
	(0.101)

TABLE 9 (Continued)

Variables	Constrained/not constrained
Control variables	Yes
Sector fixed effects	Yes
Year fixed effects	Yes
Regional fixed effects	Yes
Observations	1,550,707

Note: This table reports the dynamic effects of the dependent variable surrounding the support factor (SF) signing year. Specifically, we replaced D.After SF with a dummy variable representing each year in the [−4, +4] event window. In the model, the omitted period (benchmark period) is Year 0 (the supporting factor signing year). Year −1 is 1 year before the introduction of the supporting factor, and Year 1 is 1 year after the supporting factor signing year.

Standard errors in parentheses.

***$p < .01$; **$p < .05$; *$p < .1$.

on the dependent variables. In the model, the omitted period (benchmark period) is 0. We find that the coefficients of the interactions between D.MSME and the year dummies before the introduction of the SF are not statistically significant, suggesting no difference in the trends of the probability of being tied between the treatment and control firms before the SF; therefore, the parallel trends assumption is valid. In addition, the coefficients of the interactions between D.MSME and the year dummies after the SF show that the probability of being tied remains unchanged for MSME firms up to 4 years after the introduction of the SF. This evidence suggests that SF did not have the desired effects on MSMEs' ability to access credit.

To further alleviate concerns that our DiD design fails to capture the effect of SF and reflects the failure to consider time variables, we conduct a placebo (falsification) test following Bae et al. (2021). Through a stratification process by year, we randomly assign firms in our sample to the treatment and control groups and construct a PSEUDO D.MSME variable, which is a dummy variable that randomly assigns a value of 1 for firms in the treatment group and 0 for firms in the control group. To examine the distribution of the coefficient estimates and z-statistics of PSEUDO D.MSME after the introduction of the SF, we interacted the variable PSEUDO D.MSME with our dummy D. After SF and re-estimated Equation 3 in Table 4 by replacing D.MSME and D.MSME × D.After SF with a set of randomized PSEUDO D.MSME values and with PSEUDO D.MSME × D.After SF, the process was repeated 1000 times. This generates a simulated distribution of coefficients and z-statistics under the assumption that the introduction of the SF has no effect on the probability of being constrained. Table 10 presents the results of the placebo tests. The distribution of estimates on PSEUDO D.MSME × D.After SF shows a mean of −0.0009, which is statistically insignificant. The distribution of the z states exhibited a similar pattern. Overall, the test confirms the hypothesis that PSEUDO D.MSME × D.SF has no effect on the probability of constraint, even with simulated data. Specifically, our findings indicate a 1% chance that our results on the effects of SF on the probability of being constrained are incorrect. Marginal effects of the variables and their interaction have been estimated and can be found in the Supporting Information Material.

TABLE 10 Placebo test.

	Distribution by percentiles of estimates of PSEUDO SF effects										
	Effective	**Mean**	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
Coefficients of PSEUDO D.MSME × D.After SF	0.0295	−0.0009	−0.0935	−0.0628	−0.0534	−0.0288	−0.0005	0.0264	0.0499	0.0676	0.0941
z-stat of PSEUDO D.MSME × D.After SF	0.5	−0.0273	−2.4379	−1.6207	−1.3753	−0.7495	−0.0133	0.6862	1.2733	1.7186	2.4020

Note: The results of placebo tests. Through a stratification process by year, we randomly assign firms in our sample to the treatment and control groups and construct a PSEUDO D.MSME variable, which is a dummy variable that randomly assigns a value of 1 for firms in the treatment group and 0 for firms in the control group. We interact the variable PSEUDO D.MSME with our dummy D.After SF, we re-estimate Equation 3 in Table 4 by replacing D.MSME and D.MSME × D.After SF with a set of randomized PSEUDO D.MSME values and PSEUDO D.MSME × D.After SF, we repeat the process 1000 times. This generates a simulated distribution of coefficients and *z*-statistics under the assumption that the introduction of the SF has no effect on the probability of a constraint.

Abbreviation: SF, supporting factor.

5 | CONCLUSIONS

Our results suggest that the probability of MSMEs having less access to credit than large enterprises remains high, even after the application of SF. Business rationing mainly affects microenterprises, thus generating a crowding-out effect and competitive inequality in countries where production and business cycles are highly dependent on small enterprises. Moreover, with the introduction of regulatory measures, banks gained an overall advantage from small loan portfolios, which might not have been passed on to the economic system. One factor that makes MSMEs much more likely than large firms to be crunched is the positive relationship between asset correlation and PD. This result contrasts with the regulatory assumption that, unlike loan portfolios, the correlation should be negative. Therefore, unless the mechanisms underlying the regulatory formula introduced to improve access to credit for MSMEs are corrected, credit support instruments such as those introduced in Article 501 of the capital requirements regulation will not fully achieve their objectives. The combination of SF and regulatory correlations generates adverse selection behavior, because capital benefits provide better diversification when the portfolio is oriented towards lower-quality borrowers. This may explain how numerous medium- and low-rated companies have nevertheless attracted funding because of the incorrect calibration of regulatory models. Thinking of protecting, at least financially, the real economy and, in particular, MSMEs with a SF is not sufficient if the correlations existing in credit portfolios are not adequately considered.

The results of our analysis are particularly relevant in light of the decision to extend the SF measure to small enterprises. First, one European measure taken in the aftermath of the Covid-19 pandemic was to maintain the SFs for MSMEs and extend them to infrastructure financing, given their relevance in reducing cyclicality in the economy. More recently, the European Banking Authority emphasized the importance of the green asset ratio (GAR). This is the ratio of a bank's loans and securities that meet the EU's environmental taxonomy (including European green bonds) to most assets in the bank's balance sheet portfolio. This indicator will become a key tool for understanding how institutions finance sustainable activities and achieve the goals of the Paris Agreement. As part of the EU Action Plan, prudential supervision will be redesigned to include incentives to accelerate the process of achieving the sustainability goals set out in the UN 2030 agenda.

However, based on the evidence from our research, if this measure is not properly calibrated to other elements that condition bank choices, it could paradoxically weaken bank resilience and fail to generate the desired stimulus for sustainable growth. As has often been argued at least from a banking perspective (Financial Times “Jamie Dimon warns capital rules pose significant economic risk,” September 20, 2022), a very volatile treatment of capital requirements is a limitation of the ability to lend, especially to small businesses. Moreover, the tightening of capital rules has pushed more lending out of the regulated banking sector with an increase in lending by nonbank lenders. In the mortgage market, for example, according to the publication Inside Mortgage Finance, nonbank lenders now provide the majority of loans. Proponents argue that this has pushed riskier loans away from banks, increasing stability risk and higher costs, since shadow banking firms have higher funding costs than banks. However, large systemic institutions have higher capital requirements, which may constrain access opportunities for smaller borrowers. The extension of the SF instrument to other purposes, as in the case of the GAR, imposes caution on new verifications when empirical evidence can be gathered. Moreover, the study applies to the Italian case; however, given the weight of small and very small enterprises in the overall economy, further comparative analysis is required in countries where the structural characteristics and factors determining credit portfolio risks may be different.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data used in this study are available on request. Interested researchers can contact Giampaolo Gabbi at giampaolo.gabbi@sdabocconi.it to inquire about access to the data. Due to confidentiality and privacy considerations, certain restrictions may apply to the release of the data. Data availability is subject to ethical and legal requirements. This research was supported by the SDA Bocconi School of Management with data availability. The authors would like to thank the Institution for the financial support that enabled us to carry out this study. The Institution had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. This paper benefited from the valuable comments of Richard Levich. Special thanks are due to the referees and to Sabri Boubaker (Editor-in-Chief) for their helpful comments. Finally, we would like to thank Arsenio Stabile for his valuable help in providing some methodological support.

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ENDNOTES

[1] In the paper we adopt the European definition (EU recommendation 2003/361) of micro-, small-, and medium-sized enterprises. The main factors that determine whether an enterprise is an micro, small, and medium enterprises are: (a) the headcount (<10 for micro; <50 for small; <250 for medium-sized); (b) the turnover (<€2 mL for micro; <€10 mL for small; <€50 mL for medium) or the balance sheet total (<€2 mL for micro; <€10 mL for small; <€43 mL for medium).

[2] Since 2009, the survey has been conducted every 6 months, providing valuable insights into the financing needs and constraints of businesses over a 6-month period. Since 2013, the European Commission has been responsible for conducting one wave of the survey in all 28 countries of the European Union, while the European Central Bank conducts the other wave specifically for the 11 countries of the euro area.

[3] In Table A5 we also report the results of collinearity diagnostics. More in detail, we show the values of the common indicators of collinearity (variance inflation factor and tolerance). Both indicate that there are non-collinearity problems between the main variables in our regressions.

[4] The inverse relationship between asset correlation and default probability assumed by the Basel Committee is expressed by the following formula:

$$\rho_{PD} = 0.12 \times \frac{1-\exp(-50 \times PD)}{1-\exp(-50)} + 0.24 \times \frac{1-(1-\exp(-50 \times PD))}{1-\exp(-50)}$$

where ρ_{PD} is bounded within the interval [0.12, 0.24]. Banks applying the internal rating-based approach are allowed to adjust the previous formula for micro, small, and medium enterprises (MSMEs') exposure (smaller than 50 million euros in sales) as follows:

$$\rho_{PD} = 0.12 \times \frac{1-\exp(-50 \times PD)}{1-\exp(-50)} +0.24 \times \frac{1-(1-\exp(-50 \times PD))}{1-\exp(-50)} - 0.04 \times \left(1 - \frac{S-5}{45}\right)$$

where ρ denotes the asset correlation among borrowers (i.e., intensity of comovements among them), and is defined as the sensibility to a common risk factor, PD = the probability of default, and $0.04 \times \left(1 - \frac{S-5}{45}\right)$ represents the size adjustment factor to calculate the capital relief for MSMEs with a turnover of less than €50 million.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

See Table A1

Table A2 shows the size class distribution of firms classified as captive or noncaptive when the creditworthiness control variable is considered. The data show an inverse relationship between risk and firm size. In particular, the percentage of downgraded firms increases as firm

TABLE A1 Definitions of variables used in empirical analysis and sources.

Variables	Definitions	Source
Constrained	Constrained is a dummy variable that takes value 1 when a firm is financially rationed and 0 otherwise.	Authors' elaboration.
D.MSME	D.MSME is a dummy variable that takes value 1 when firm is belonging to the MSME segment and 0 otherwise.	Authors' elaboration on Aida Bureau Van Dijk database.
D.AFTER SF	D.After SF is a dummy variable that equals one after that SF came into force and zero otherwise.	Authors' elaboration.
D.Micro	D.Micro is a dummy variable that takes value 1 when firm falls within the microsize class and 0 otherwise.	Authors' elaboration on Aida Bureau Van Dijk database.
D.Small	D.Small is a dummy variable that takes value 1 when firm falls within the small size class and 0 otherwise.	Authors' elaboration on Aida Bureau Van Dijk database.
D.Medium	D.Medium is a dummy variable that takes value 1 when firm falls within the medium size class and 0 otherwise.	Authors' elaboration on Aida Bureau Van Dijk database.
Age	The variable measures the time between the initial creation of a firm and the present time (in years).	Authors' elaboration on Aida Bureau Van Dijk database.
Profitability	Profitability is the earnings before interest and taxes of the company relative to its total assets.	Authors' elaboration on Aida Bureau Van Dijk database.
RR GdP GR	The variable refers to the growth rate of regional real gross domestic product.	Bank of Italy Statistics.
NPLs rate	The ratio between the annual flow of adjusted nonperforming loans and the stock of performing loans of the previous year.	Bank of Itay Statistics.
Loans to NFCs HH to GdP	Loans to HHs and NFC as a proportion of gross domestic product.	Bank of Itay Statistics.
Regulatory asset correlation (RC)	The variable measures the intensity of comovements among borrowers and is defined as the sensibility to a common risk factor. The values comes from the application of following formula: $R_{\text{Sme}} = 0.12 \times \frac{(1-e^{-50\text{PD}})}{(1-e^{-50})} + 0.24 \times \left[1 - \frac{(1-e^{-50\text{PD}})}{(1-e^{-50})}\right] - 0.04 \times \left(1 - \frac{S-5}{45}\right).$	Vozzella and Gabbi (2020). What is good and bad with the regulation supporting the SME's credit access. *Journal of Financial Regulation and Compliance* 28 (4): 569–586.
Empirical asset correlation (EC)	The variable measures the intensity of comovements among borrowers and is defined as the sensibility to a common risk factor. After computing the probability of default (PD_i) and joint probability of default (JDP_{ii}), the values are drawn by applying the bivariate Gaussian Copula.	Vozzella and Gabbi (2020). What is good and bad with the regulation supporting the SME's credit access. *Journal of Financial Regulation and Compliance* 28 (4): 569–586.

Abbreviations: GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan; SF, supporting factor.

TABLE A2 Firm's credit-worthiness by "status" and size class.

	Large	Medium	Small	Micro	Total
Not constrained					
Score (upgraded)	2930	30,456	88,078	229,196	350,660
Percentage by size	0.84	8.69	25.12	65.36	100
Percentage by score	22.71	27.19	29.85	30.75	30.09
Score (unchanged)	6382	55,323	143,021	336,189	540,915
Percentage by size	1.18	10.23	26.44	62.15	100
Percentage by score	49.47	49.39	48.46	45.11	46.42
Score (downgraded)	1951	22,318	65,606	183,836	273,711
Percentage by size	0.71	8.15	23.97	67.16	100
Percentage by score	15.12	19.92	22.23	24.67	23.49
Total	12,900	112,022	295,118	745,246	1,165,286
Constrained					
Score (upgraded)	1024	9175	28,192	91,381	129,772
Percentage by size	0.79	7.07	21.72	70.42	100
Percentage by score	23.30	27.04	28.25	26.95	27.19
Score (unchanged)	1965	15,369	43,917	135,593	196,844
Percentage by size	1.00	7.81	22.31	68.88	100
Percentage by score	44.72	45.30	44.00	39.99	41.25
Score (downgraded)	1220	9565	30,896	108,907	150,588
Percentage by size	0.81	6.35	20.52	72.32	100
Percentage by score	27.77	28.19	30.95	32.12	31.56
Total	4394	33,929	99,812	339,069	477,204

Note: The size class distribution of firms classified as constrained or unconstrained when we consider a firm's creditworthiness. Upgrades refer to firms that have experienced improvements in credit strength. Conversely, a downgrade indicates that the firm experienced a downward revision in credit quality. Finally, the unchanged is attributed to firms that remained in the same creditworthiness class. The reference period was 2007–2017.

Source: Authors' elaboration on Aida Bureau Van Dijk database.

size decreases, both when considering unencumbered firms and, even more so, when referring to captive firms. The data confirm that the probability of being tied increases with risk and, given the inverse relationship between risk and size, it is higher for micro and small firms.

Descriptive statistics with respect to the age and profitability of the firms in our sample, both of which were used as control variables in our regressions, are shown in Table A3. Profitability is the earnings before interest and taxes of a company relative to its total assets. Notably, the average profitability value increases with size, as is the case for both constrained and nonconstrained firms. Interestingly, the average values recorded are very similar between the two categories, but while the average values for large and microfirms are higher for nonconstrained firms, small and medium firms show the opposite behavior. This suggests that

TABLE A3 Statistics on firm's characteristics by size and classified as constrained and not constrained.

	Not constrained					Constrained				
	Mean	Standard deviation	First quartile	Median	Third quartile	Mean	Standard deviation	First quartile	Median	Third quartile
Profitability										
Large	5.1	6.5	−2.1	4.1	5.9	4.9	7.0	−2.6	3.9	5.9
Medium	4.3	5.5	−1.5	3.5	4.8	4.5	6.3	−2.1	3.5	4.8
Small	4.6	5.6	−1.3	3.8	5.6	4.7	6.2	−1.7	3.7	5.1
Micro	5.0	6.4	−2.2	3.9	5.1	4.7	6.7	−2.2	3.7	5.6
Age										
Large	36.0	17.3	17.5	34.0	38.9	35.5	17.2	17.7	33.0	38.7
Medium	35.5	15.6	17.7	34.0	38.9	35.3	15.7	17.8	34.0	39.0
Small	30.7	14.2	15.6	29.0	33.4	30.6	14.3	15.7	29.0	33.4
Micro	24.0	11.9	12.4	21.0	24.3	23.8	12.0	12.5	21.0	24.3

Note: The summary statistics of the profitability and age of the firms in our sample. Values are divided by size class to distinguish between constrained and unconstrained firms. Profitability is the earnings before interest and taxes of a firm relative to its total assets. Age was expressed in years. The mean is the average of the data values. Standard deviation is the standard deviation of the sample. It measures the average distance between a single observation and its mean. The median (or 50th percentile) is the "middle number" of the sorted data values. The first quartile refers to the data value in which 25% of the observations are less than. The third quartile is the value at which 25% of the observations lie above and 75% lie below that value. The sample spans the 2007–2017 window.

Source: Authors' elaboration on Aida Bureau Van Dijk database.

TABLE A4 Summary statistics on regional control variables.

Region	RR GdP GR					NPLs rate					Loans to NFCs & HHs to GdP				
	Mean	Standard deviation	Minimum	Median	Maximum	Mean	Standard deviation	Minimum	Median	Maximum	Mean	Standard deviation	Minimum	Median	Maximum
Northern Italy															
Emilia-Romagna	−0.015	2.66	−6.91	0.9	2.57	3.59	1.42	1.31	3.42	5.63	69.4	5.70	57.27	70.98	75.63
Friuli-Venezia Giulia	−0.570	2.96	−7.23	0.08	3.05	2.89	1.00	1.09	2.87	3.75	49.5	3.26	42.26	49.59	53.81
Liguria	−0.951	2.36	−6.49	−0.23	2.32	3.15	1.44	1.38	2.78	5.7	41.3	3.68	33.01	42.16	45.47
Lombardy	0.134	2.78	−6.1	0.67	4.47	2.58	1.00	1.12	2.61	4.58	72.1	6.08	59.16	73.55	80.47
Piedmont	−0.717	3.14	−8.42	0.81	3.62	2.60	.775	1.4	2.58	3.83	46.7	2.57	41.94	47.48	50.02
Trentino-South Tyrol Adige	0.640	1.31	−2.65	0.75	2.73	2.99	.711	1.15	2.97	3.85	72.8	3.95	66.36	71.16	78.22
Aosta Valley	−1.25	3.07	−6.39	−0.71	4.72	2.99	2.25	0.82	3.07	8.44	37.1	1.17	34.78	37.44	38.61
Veneto	−0.241	2.45	−5.86	0.45	2.27	3.28	1.10	1.61	3.17	5.58	66.4	5.63	52.51	68.24	71.95
Mean	−0.371	2.59	−6.16	0.34	3.22	3.01	1.21	1.23	2.93	5.17	56.9	4.01	48.41	57.57	61.77
Centre															
Tuscany	−0.360	1.76	−4.04	0.76	1.63	3.81	1.37	1.47	4.39	6.23	61.7	3.32	55.29	63.45	65.21
Umbria	−1.55	2.89	−8.21	−0.78	2.83	4.26	1.28	1.86	4.37	5.64	61.0	4.19	51.65	63.31	65.25
Marche	−1.02	2.10	−4.94	−0.19	1.74	5.00	2.51	2.02	3.98	9.92	64.8	4.99	53.07	66.42	70.54
Lazio	−0.512	1.96	−3.64	−0.16	2.55	3.31	.980	1.44	3.23	4.9	55.7	4.61	46.85	56.15	61.12
Mean	−0.862	2.18	−5.21	−0.09	2.19	4.09	1.54	1.7	3.99	6.67	60.8	4.28	51.72	62.33	65.53

TABLE A4 (Continued)

Region	RR GdP GR					NPLs rate					Loans to NFCs & HHs to GdP				
	Mean	Standard deviation	Minimum	Median	Maximum	Mean	Standard deviation	Minimum	Median	Maximum	Mean	Standard deviation	Minimum	Median	Maximum
Southern Italy and Islands															
Abruzzo	−0.310	0.024	−6.2	0.07	2.48	4.89	1.58	1.8	5.36	6.74	48.6	2.46	42.74	49.19	51.29
Basilicata	0.208	0.035	−5.9	0.67	9.03	4.09	1.36	2.03	3.65	6.16	34.6	2.38	30.3	35.23	37.54
Calabria	−1.33	0.018	−4.1	−0.89	1.3	4.54	1.34	2.32	4.18	6.95	26.3	1.68	23.04	27.17	28.32
Campania	−1.11	0.020	−4.99	−1.41	1.66	4.55	1.76	2.18	4.06	7.58	36.3	2.31	32.09	36.73	39.46
Molise	−2.11	0.027	−7.22	−1.33	1.88	4.78	2.30	1.79	4.17	9.13	34.3	2.18	28.39	35.35	36.02
Apulia	−0.710	0.018	−4.72	0.25	1.22	3.84	1.08	2.19	3.6	5.48	38.4	2.94	32.29	39.18	41.52
Sardinia	−0.932	0.018	−4.55	−0.65	1.81	3.83	1.32	1.68	3.71	5.74	37.7	1.71	34.41	37.98	40.3
Sicily	−1.36	0.015	−4.37	−1.7	0.7	4.32	1.09	2.29	4.59	5.63	33.0	2.45	28.84	32.77	35.83
Mean	−0.956	0.022	−5.26	−0.62	2.51	4.36	1.48	2.04	4.16	6.68	36.1	2.26	31.51	36.7	38.78

Note: The summary statistics of the regional control variables. RR GdP GR is the real growth rate of the regional gross domestic product. The NPLs rate is the ratio of the annual flow of adjusted NPLs to the stock of performing loans in the previous year (NPLs ratio). Loans to NFCs and HHs to GDP refer to loans to HH and NFC as a proportion of the GDP. The mean is the regional average of the data. The standard deviation was the standard deviation at the regional level. The median (or 50th percentile) is the “middle number” of the sorted data values. The reference period was 2007–2017

Abbreviations: GDP, gross domestic product; HH, household; NFC, nonfinancial corporation; NPL, nonperforming loan.

Source: Authors' elaboration on Bank of Itay Statistics.

TABLE A5 Collinearity diagnostics.

Variables	VIF	SQRT VIF	Tolerance	R^2
D.MSME	2.35	1.53	0.4249	.5751
EC	2.35	1.53	0.4248	.5752
RC	1.47	1.21	0.6817	.3183
Age	1.12	1.06	0.8958	.1042
RR GdP GR	1.38	1.17	0.7258	.2742
Loans to NFCs HH to GdP	1.02	1.01	0.9761	.0239
NPLs rate	1.40	1.18	0.7152	.2848
Profitability	1.00	1.00	10.000	.0000
Mean VIF	1.51			

Note: The results of the collinearity diagnostics. The values of the common indicators of collinearity, the VIF and tolerance, indicate that there are no collinearity problems between the main variables in our regressions. Multicollinearity is generally indicated by individual VIF values greater than 10 and an average value greater than 6. The absence of multicollinearity problems was also confirmed by the significant nonzero values of the tolerance indicator.

Abbreviations: GDP, gross domestic product; HH, household; MSME, micro, small, and medium enterprises; NFC, nonfinancial corporation; NPL, nonperforming loan; VIF, variance inflation factor.

factors favoring access to credit are not exclusively related to firm performance. The age statistics show that age increases with firm size regardless of its “status” (constrained or not constrained). It is worth noting that all measures of distributional variability show perfectly overlapping values between constrained and unconstrained firms.

Finally, we also show details on the regional control variables (Table A4). In many countries characterized by geographical imbalances, it is relevant to include this element, which conditions both business and credit cycles. In Italy, we included 20 administrative regions into which the territory is divided. There were significant differences between various geographical areas in Italy. Although, on average, the growth rates of the gross domestic product in the period considered were negative in almost all regions, the performance of the regions in Southern Italy was much worse. At the same time, if we consider the ratio between the annual flow of adjusted nonperforming loans (NPLs) and the stock of performing loans in the previous year (NPLs rate), we find that the rate of NPLs in Southern Italy (4.36) is about 50% higher than that of the North (3.00) and 30% higher than that of the Center (4.1). On the other hand, data on loans to households and nonfinancial corporations as a proportion of gross domestic product (loans to nonfinancial corporations and households to GdP) show that while the ratio is close to 60% in both the North and the Center of Italy, in the South, it is less than 40%. Overall, the picture that emerges is one of a country with strong territorial differences, which it is plausible to assume plays a crucial role in MSME′ access to credit. This is also confirmed by the results of our regressions, where both the control variables referring to regional characteristics and the control variables in the form of fixed effects always reveal the expected and highly statistically significant signs.

In Table A5 we show the results of collinearity diagnostics. More in detail, we show the values of the common indicators of collinearity (variance inflation factor and tolerance). Both indicate that there are noncollinearity problems between the main variables in our regressions.