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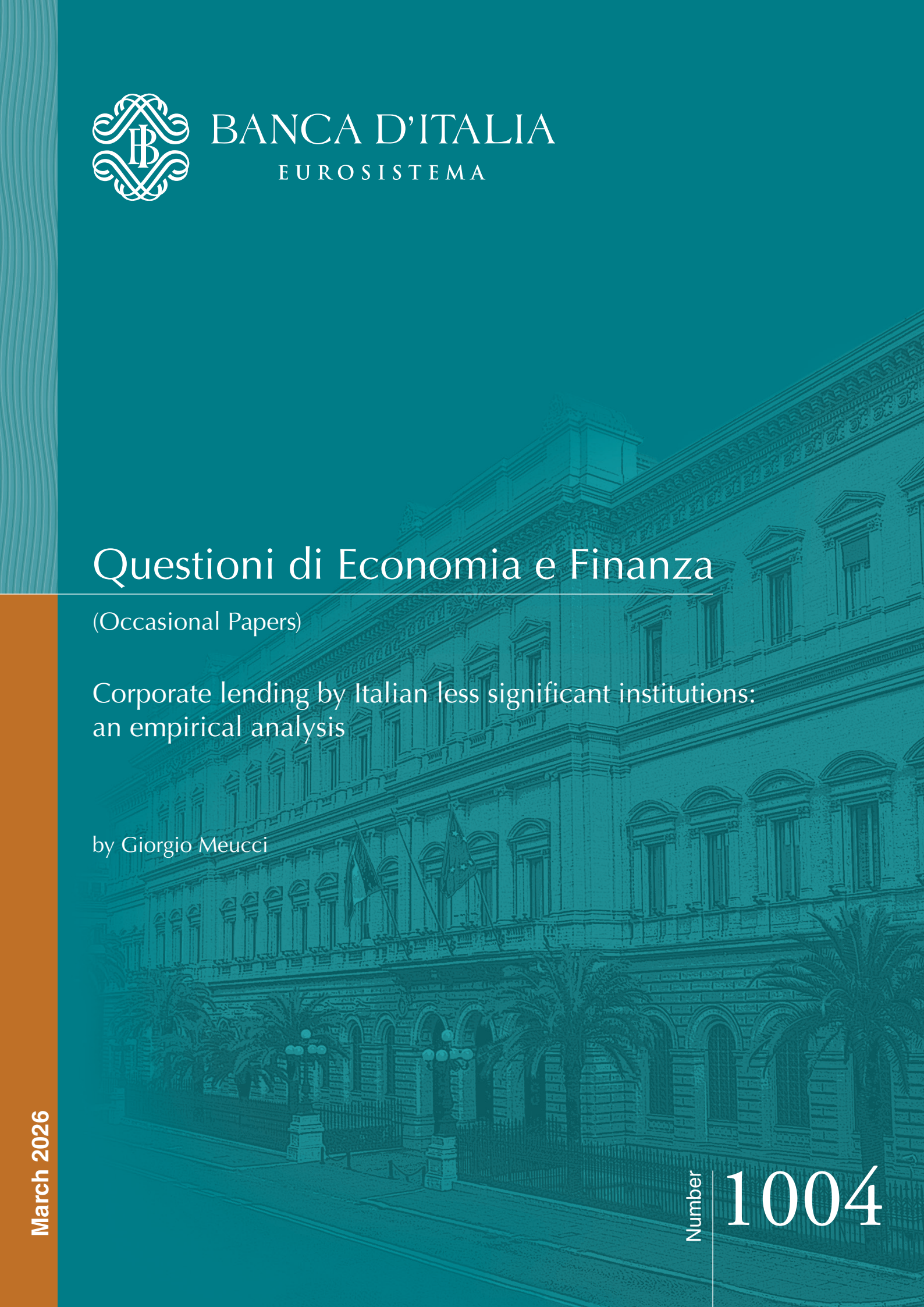

Questioni di Economia e Finanza

(Occasional Papers)

Corporate lending by Italian less significant institutions: an empirical analysis

by Giorgio Meucci

March 2026

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CORPORATE LENDING BY ITALIAN LESS SIGNIFICANT INSTITUTIONS: AN EMPIRICAL ANALYSIS

by Giorgio Meucci*

Abstract

This study examines the reasons behind the higher default rates of loans granted by Italian banks categorized as less significant institutions (LSIs) under the Single Supervisory Mechanism compared with those issued by significant institutions (SIs). Using loan-level data matched with firm characteristics, the analysis shows that LSIs tend to serve smaller and riskier firms, which explains much of the observed default differential. After controlling for firm and loan characteristics, the remaining difference is substantially reduced. The pricing applied by LSIs appears broadly aligned with that of SIs, conditional on observable factors. These findings suggest that LSIs may facilitate access to credit for firms with potentially more limited financing opportunities.

JEL Classification: G21, E51, D22.

Keywords: credit quality, corporate finance, less significant institutions, interest rates.

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1. Introduction[1]

In Italy, since 2017, the default rate of loans granted by banks categorized as less significant institutions (LSIs) by the Single Supervisory Mechanism[2] (SSM) has consistently exceeded that of significant institutions (SIs). This discrepancy persists when restricting the analysis to loans to Italian non-financial corporations (NFCs).

The study pursues two main objectives. First, it investigates the profile of firms borrowing from either of the two categories of banks and explores the underlying factors driving the difference in default rates between them, assessing whether this gap can be explained by observable firm, loan and intermediary characteristics. Should the difference persist after accounting for these characteristics, this would point to the role of unobserved factors, such as differences in business strategies, portfolio management efficiency, or unobservable characteristics of the borrowing firms themselves. Second, the analysis investigates whether LSIs' pricing policies are aligned with those of SIs, or whether they tend to charge different interest rates for equivalent risk profiles. This approach helps understand LSIs credit allocation strategy, potentially catering to segments of the market that are underserved by larger banks.

To investigate these issues, a loan-level dataset is constructed by merging data from AnaCredit (covering the period 2021-2024) with firm-level financial information from the Cerved data base, along with characteristics of the reporting intermediaries, drawn from harmonized supervisory reporting (FINREP and COREP).

Based on this dataset, regression analysis from three models yields the following main findings: i) *ex-ante* riskier and smaller firms, as well as those exhibiting lower levels of liquidity, are more likely to include an LSI among their lenders; ii) a substantial part of the difference in the aggregate loan default rate between LSIs and SIs is explained by the characteristics of the loans and the borrowing firms; iii) conditional on firm, loan and intermediary characteristics, the pricing applied by LSIs and SIs appears broadly similar.

[1] The author would like to thank Paolo Angelini, Alessio De Vincenzo, Emilia Bonaccorsi di Patti, Alessio Anzuini, Raffaella Pico, and Federica Ciocchetta for their valuable comments. The views expressed are solely those of the author and do not necessarily reflect those of the Bank of Italy.

[2] The criteria for determining whether intermediaries are considered Significant Institutions - and therefore under the ECB's direct supervision - are set out in the SSM Regulation and the SSM Framework Regulation. These criteria include the bank's size, its importance to the economy of its home country or the EU as a whole and the significance of its cross-border activities. In contrast, Less Significant Institutions (LSIs) are directly supervised by their national competent authorities, under the oversight of the ECB.

Furthermore, to gain deeper insights into LSIs' credit allocation strategies, we examined loan applications recorded in the Credit Register's Initial Information Service (IIS)[3], which documents enquiries about new loan applicants submitted by intermediaries. The analysis reveals that, all else being equal, LSIs are more likely to approve loan applications than SIs. In other words, LSIs exhibit a greater willingness to grant credit, irrespective of firm characteristics, conditional on having received a loan application. The interpretation of these data is subject to a number of caveats, therefore the detailed findings are provided in the Annex.

The remainder of this paper is structured as follows. Section 2 reviews the related literature and outlines the main contributions of this study. Section 3 presents the dataset used in the analysis, detailing its construction and coverage. Section 4 describes the empirical methodology, with a particular focus on the specification of the regression models. Section 5 reports and discusses the main results. Section 6 concludes.

2. Related literature

While the role of small, local, and relationship banking has been widely studied, this paper contributes to the literature by offering a systematic assessment of credit risk profiles and lending policies within the institutional framework of the SSM, which explicitly distinguishes between SIs and LSIs.

A substantial body of research highlights the comparative advantage of local banks in acquiring and processing soft information through repeated interactions with borrowers and close ties to the local community. Berger and Udell (2002) argue that, under relationship lending, local intermediaries accumulate valuable knowledge about firm dynamics, ownership structures, and local networks, which can be leveraged in credit decisions. This informational advantage may lead to more efficient credit allocation and improved borrower screening. In this context, the findings of Bolton et al. (2013) are particularly relevant: financial institutions with strong pre-crisis lending relationships applied higher spreads before the Global Financial Crisis, but subsequently offered more favourable continuation lending terms and experienced lower default rates.

[3] Enquiries have been used as an indirect proxy for loan demand in several studies published by the Bank of Italy. Notably, Albertazzi, Bottero, and Sene (2014) find that firms rejected in previous credit applications are more likely to succeed in subsequent attempts if they persist. Bonaccorsi di Patti and Sette (2016) show a positive relationship between the extent to which banks tighten credit to NFCs and the share of securitized loans. Alessandri and Bottero (2017) report that increased aggregate uncertainty reduces the probability of loan approval. Galardo, Lozzi, and Mistrulli (2019) emphasize the mitigating role of social capital in the face of rising uncertainty. Finally, Bottoni et al. (2022) find that firms in the South are less inclined to seek credit, discouraged by higher costs and stricter collateral requirements.

Among the many studies on Italian banks, Albareto et al. (2022) provide further evidence on the strategic importance of local banks, especially in Southern Italy. Between 2008 and 2019, local institutions played a key role in sustaining credit supply to Southern firms, despite their relatively weaker creditworthiness and the higher costs and collateral demands they face.

Additional studies from the United States reinforce the view that smaller, local banks are particularly important for supporting small business lending. Mkhaiber and Werner (2021) find an inverse relationship between bank size and the propensity to lend to small and micro enterprises. Similarly, Cole (2018) documents that the decline in small-business lending during and after the financial crisis was significantly more pronounced for large banks than for small banks. In the same vein, Berger et al. (2017) suggest that small banks have comparative advantages in alleviating credit constraints, particularly during adverse economic conditions. Nguyen and Barth (2020) provide further evidence by showing that community banks consistently supplied more small business loans than non-community banks. Finaldi et al. (2022) show that, in the Italian market, credit standards tightened particularly for micro-enterprises, while large firms were largely unaffected. These stricter lending criteria were primarily applied by larger banks and by institutions with weaker balance sheets.

Stefani et al. (2016) suggest that the overall credit risk exposure of financial institutions is also influenced by unobserved managerial and organizational factors, which may limit the ability of small banks to manage risk effectively. This is particularly relevant in the context of LSIs, whose performance is marked by significant heterogeneity. Guarino and Oliva (2024) show that inefficiencies in cost management are not a systemic feature of the LSIs, but rather stem from the behaviour of a subset of traditional banks.

The main contribution of this paper lies in extending the analysis of small banks' credit risk profiles and lending behaviour, an area that remains central to understanding credit allocation dynamics. The regulatory distinction between SIs and LSIs provides a valuable framework through which to examine these issues in a systematic way. To the best of the author's knowledge, this represents the first study to compare firms borrowing from the two categories of banks and to analyze the determinants of default rates across them, thereby offering broader insights into the role of smaller intermediaries within the credit market.

3. Data

Since mid-2017, the default rate of loans granted by Italian LSIs has consistently exceeded that of SIs (Figure 1, Panel A). The study focuses on loans granted to Italian NFCs (which account for 45 per cent of the total outstanding amount as of the end of 2024) for which the observed general pattern remains valid (Figure 1, Panel B).

For the analysis, a loan-level dataset is constructed using AnaCredit data covering the period 2021–2024. For each reference year, the dataset comprises all loans classified as performing at the end of previous year.[4] This dataset is enriched with firm-level financial information from the Cerved database and with balance sheet data of the reporting banks, drawn from harmonized supervisory reporting (FINREP and COREP). Cerved firms cover around 80 per cent of the total amount. The analysis excludes specialized intermediaries[5] (representing approximately 1 per cent of observations), as their business model is primarily oriented towards the management of non-performing loans. The final dataset consists of approximately 2.6 million observations, 86 per cent of which refer to loans issued by SIs. It includes 170 intermediaries, of which 51 are classified as LSIs, 23 as SIs or members of SI groups, and 96 cooperative banks (BCCs) affiliated with SI groups.[6] The latter are therefore considered part of the SIs, accounting for only 18 per cent of SI observations in the sample. Table 1 reports the main descriptive statistics of the variables considered.

A *default* indicator is defined as taking the value 1 if the loan becomes non-performing during the reference year. The dataset indicates that the average default rate in the sample (i.e. the mean value of the *default* dummy) is 1.68 per cent for LSIs and 1.23 per cent for SIs[7] (Figure 2, Panel A).

With regard to pricing, a *spread* variable is constructed for each loan in the dataset, to capture the cost of credit relative to a market benchmark. For fixed-rate loans, it is defined as the difference

[4] We consider only loans extended by SIs and LIs intermediaries, larger than 10,000 euros, and classified in "other loans" category, which represent around 80 per cent of the total amount and excludes overdrafts, trade receivables, credit card debts and other revolving debts.

[5] Specialized intermediaries are engaged in the management of non-performing loans, consumer credit, leasing, factoring, and payment services.

[6] Gruppo Iccrea and MedioCredito Centrale are Significant Institutions that include numerous Italian BCCs.

[7] This figure differs from the default rate typically reported, and shown in Figure 1, for several reasons: (i) it is calculated on a per-loan basis, whereas the standard default rate is based on loan amounts; (ii) it is computed on an annual basis, while the standard rate is a quarterly figure annualized and seasonally adjusted; (iii) it refers to the subsample of firms covered in the Cerved data base; (iv); it includes only loans granted either by an SI or an LSI I; (v) the scope of the analysis is a sample of AnaCredit loans, whereas the standard rate is computed using the loans reported to the Credit Register, which follow a different reporting threshold and involve a different set of reporting intermediaries.

between the interest rate at origination and the 10-year IRS rate that was in effect at that time, while for variable-rate loans it is calculated as the difference between the interest rate observed at the conclusion of the reference year and the 3-month Euribor rate on the same date. The average *spread* applied to loans is 2.22 percentage points for LSIs and 2.03 for SIs (Figure 3, Panel A), suggesting that, on average, LSIs charge a higher cost of credit compared to SIs.

At this stage, it would be pertinent to consider the extent to which the outcomes are influenced by the presence of BCCs within the SI groups. Furthermore, it would be worthwhile to explore whether these intermediaries exhibit characteristics more akin to traditional SIs or LSIs with respect to credit risk and pricing behaviour. Focusing specifically on the 96 cooperative credit banks reporting to AnaCredit and belonging to SI groups, their average default rate is closer to that of traditional SIs than to LSIs, while the average *spread* they apply remains more aligned with that of LSIs. (Figure 2 and Figure 3, Panel B).

As expected, both the average default rate and the average *spread* in the full sample are higher for riskier and smaller firms, and for those located in central or southern regions of Italy (Panels C-E).

4. Methodology

In the following, the study investigates the profile of firms that obtain loans from LSIs, and then assess whether, given the characteristics of their portfolios, loans granted by LSIs exhibit a higher default rate compared to those originated by SIs. To address these questions, the previously described loan-level dataset is utilized and two logistic regression models are specified.

$$log\left(\frac{P(LSI_{l,i,b,t}=1)}{P(LSI_{l,i,b,t}=0)}\right) = \beta_0 + \beta' X_{i,t-1}^{firm} + \theta_t + \xi_s + \psi_p + \varepsilon_{l,i,b,t} \quad (1)$$

$$log\left(\frac{P(default_{l,i,b,t}=1)}{P(default_{l,i,b,t}=0)}\right) = \beta_0 + \beta_1 LSI_{l,i,b,t} + \beta' X_{i,t-1}^{firm} + \gamma' X_{l,t}^{loan} + \delta' X_{b,t-1}^{bank} + \theta_t + \xi_p + \psi_s + \varepsilon_{l,i,b,t} \quad (2)$$

In equation (1) the dependent variable is represented by an indicator, denoted as $LSI_{l,i,b,t}$ which takes the value 1 if the intermediary *b* issuing loan *l* to the firm *i* in year *t* is categorized as an LSI, and 0 otherwise. The explanatory variables consist of a set of firm-level characteristics measured in the previous year, represented by $X_{i,t-1}^{firm}$. These include the risk score assessed using the Cerved indicator, [8] firm size class[9] and relevant balance sheet variables, already introduced in Table 1. Time fixed effects θ_t, economic sector fixed effects ξ_s, and province fixed effects ψ_p are included. This

[8] The "Score4" risk indicator by Cebi-Cerved classifies companies into four different risk categories based on models that take into account both economic-financial components from their financial statements and systemic factors.
[9] Size classes are defined according to the EU Commission's definition of micro, small, medium and large firms.

model aims to identify the factors influencing the likelihood that a firm establishes a credit relationship with an LSI rather than an SI, highlighting possible risk profiles or specific dimensional and regional attributes associated with LSI clients. Note that firms borrowing from multiple banks are represented in the dataset with one observation per loan, as each credit relationship is considered independently.

In equation (2) the dependent variable is the $default_{i,b,l,t}$ indicator, previously defined as equal to one if the loan l granted from the intermediary b to the firm i defaults during the year t. The independent variables include not only the firm characteristics $X_{i,t-1}^{firm}$, but also characteristics of the individual intermediary[10] $X_{b,t-1}^{bank}$ and also loan-specific features $X_{l,t}^{loan}$ (see once more Table 1), which also include the year of origination and whether the loan was subject to a moratorium.[11] Of particular interest is the inclusion of the $LSI_{l,i,b,t}$ indicator, whose coefficient β_1 provides a direct measure of the conditional difference in the default rate of LSIs compared to the baseline of SIs. In summary, the coefficient enables the estimation of whether loans issued by LSIs exhibit a heightened default risk when compared to those granted by SIs, holding constant other observed factors.

While descriptive evidence suggests that LSIs, on average, apply higher credit spreads than SIs (as shown in Figure 3), this pricing gap could just reflect a different risk composition or signals a distinct pricing policy. In order to address this question, a linear regression model is estimated in which the dependent variable is the loan-specific *spread*, and the set of independent variables mirrors that of equation (2).

$$Spread_{i,b,l,t} = \beta_0 + \beta_1 LSI_{i,b,l,t} + \beta' X_{i,t-1}^{firm} + \gamma' X_{l,t}^{loan} + \delta' X_{b,t-1}^{bank} + \theta_t + \xi_i + \psi_i + \varepsilon_{i,b,l,t} \quad (3)$$

The key explanatory variable remains the $LSI_{i,b,l,t}$ indicator. Should the coefficient β_1 be found to be significantly positive and economically meaningful, this would indicate that, conditional on observable firm, loan, and intermediary characteristics, LSIs consistently apply higher spreads, pointing to a differentiated pricing strategy. Conversely, an insignificant or near-zero coefficient would indicate that the *spread* differential is fully accounted for by differences in borrower and loan risk profiles, suggesting no systematic deviation in loan pricing behaviour between LSIs and SIs once these are controlled for.

[10] The NPL ratio is not included in this model, because an intermediary with a higher NPL ratio may systematically grant riskier loans, and therefore this variable could have an endogenous component relative to the dependent variable.
[11] Debt moratoria were introduced by Decree Law 18/2020 (the "Cure Italy" decree) as an extraordinary policy measure aimed at mitigating the severe liquidity constraints faced by small and medium-sized enterprises during the Covid-19 pandemic.

5. Results

In order to explore the hypothesis that certain types of firms are more likely to borrow from LSIs, we estimate the regression model outlined in equation (1). The results, summarized in Figure 4, show that, conditional on other firm characteristics, high-risk firms are significantly more likely to establish a credit relationship with an LSI than low-risk firms, with an estimated difference of +4 percentage points. This effect is economically relevant, given the baseline of 14 per cent observed in the full sample. In contrast, medium-to-large firms are less likely to borrow from an LSI compared to smaller firms (more than 1.2 percentage points lower). The probability of establishing a credit relationship with an LSI is also influenced by factors such as the firm's liquidity and leverage. For instance, at the 95th percentile of the liquidity distribution (high-liquidity firms), the expected probability of borrowing from an LSI is 1.07 percentage points lower than at the 5th percentile (low-liquidity firms), whereas at the 95th percentile of the leverage distribution, it is 0.77 percentage points higher than at the 5th percentile.

This finding indicates that the higher default rate of LSIs may be attributable the composition of the loan portfolios by borrower characteristics. When excluding cooperative banks belonging to significant banking groups from the sample, these patterns become even more pronounced in terms of the magnitude of the estimated effects (Figure 5).

The estimation of the model described in equation (2) provides additional insights, as it enables the testing of the hypothesis that loans granted by LSIs exhibit a higher default rate compared to those issued by SIs, even after controlling for firm characteristics, loan-specific features, and intermediary-level variables. This approach facilitates the evaluation of whether the observed variation in default rates can be ascribed to unobserved factors, such as the capacity to effectively manage credit portfolios, the composition of loan portfolios, or characteristics of the borrowing firms themselves not included in the estimated model.

Conditional on all observed factors, the marginal effect associated with the LSI indicator is modest (14 basis points, Figure 6, Panel A), indicating the presence of a residual component not captured by the included variables. However, this residual effect is relatively small, accounting for approximately 30 per cent of the default rate difference between LSIs and SIs observed in the descriptive analysis (45 basis points, see Figure 2). This indicates that the remaining part (approximately 70 per cent) can be attributed to observed variables, particularly ex-ante firm’s risk, liquidity, and gross operating income. Among the factors explicitly considered in the model, the unobserved component of risk (observable to the intermediary) proxied by the *spread* plays a significant role. For instance, a loan with a *spread* at the 95th percentile of the distribution (equal

to 4.54) has a default rate that is 0.84 percentage points higher than that of a loan with a *spread* at the 5th percentile (equal to 0.39). The presence of debt moratoria does not appear to constitute a significant factor, and even when loans subject to moratorium are entirely excluded from the analysis, the results remain substantially unchanged. When excluding the intermediary characteristics $X_{b,t-1}^{bank}$ from the model, the marginal effect of the indicator $LSI_{l,i,b,t}$ would increase by only 2 basis points (Figure 6, Panel B), indicating that firm and loan characteristics alone are sufficient to account for the vast majority of the observed difference.

Employing an alternative bank classification that introduces a third category for BCCs belonging to SI groups, thereby excluding them from the SIs and considering the latter as the baseline level, the marginal effect associated with the LSI group indicator is larger than in the baseline model (0.18 both when including and excluding intermediary characteristics, Figure 7), while BCCs belonging to SI groups occupy an intermediate position between LSIs and traditional SIs.

It could be the case that LSIs grant loans to riskier firms and get compensated for such higher risk, so they are positioning themselves in a different point of the risk-return frontier than SIs. As previously shown in the descriptive statistics, LSIs apply, on average, higher spreads compared to SIs (+19 basis points, see Figure 3). However, results from the estimation of equations (1) and (2) have documented that LSI portfolios are more exposed to *ex-ante* credit risk, due to the characteristics of their client firms, and that this different composition largely explains their higher *ex-post* default rates. It is therefore relevant to ask whether the higher *spread* is also observed when controlling for firm, loan, and intermediary characteristics, or whether it simply reflects the composition of their portfolios. Equation (3) addresses this question. The results, presented in Figure 8, show that conditional on all observable factors, the *spread* applied by LSIs is virtually identical to that of SIs. The marginal effect of the LSI indicator is only 1 basis point. This finding indicates that the higher average *spread* observed in descriptive statistics cannot be attributed to systematically different pricing strategies employed by LSIs. Instead, the result is consistent with the hypothesis that this elevated *spread* is attributable to the pricing of the additional risk inherent in the composition of their loan portfolios. Figure 9 shows that even when BCCs belonging to SI groups are considered separately, the marginal effect associated with the LSI group remains modest.

As a robustness check, the next analysis focuses on variable-rate loans only and their performance during 2021 and 2022, a period when overall interest rates were higher. In this sub-sample, the average difference in *spread* between LSIs and SIs increased from 19 to 47 basis points. Although

not shown for brevity, the estimation reveals that the average marginal effect associated with the LSI indicator remains modest, at 14 basis points. This suggests that, even within this sub-sample, the observed disparity is largely attributable to differences in the composition of loan portfolios.

6. Conclusions

This study investigates the underlying factors driving the systematically higher default rates observed among loans granted by LSIs in Italy, compared to those issued by SIs. By constructing a comprehensive dataset, based on loan-level data from AnaCredit, the analysis examines the composition of their NFC loans portfolio and pricing strategies.

The results suggest that the higher default rate observed among LSIs is largely explained by the characteristics of the borrowers. LSIs tend to serve smaller, riskier and less liquid firms. Once firm-level and loan-level variables are considered, the gap in default rates between LSIs and SIs is substantially reduced.

When considering loan pricing behavior, the findings suggest that although LSIs apply higher average spreads, these are largely consistent with the higher risk profile of their portfolios. Once firm, loan, and intermediary characteristics are controlled for, the difference in applied spreads between LSIs and SIs becomes negligible. This implies that LSIs adopt loan pricing strategies that are aligned with those of SIs, rather than systematically charging higher rates for equivalent risk profiles.

These findings are consistent with the hypothesis that LSIs may play a distinctive role in the credit market, facilitating access to credit for firms with potentially more limited financing opportunities.

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Figures and Tables

Table 1 – Descriptive statistics

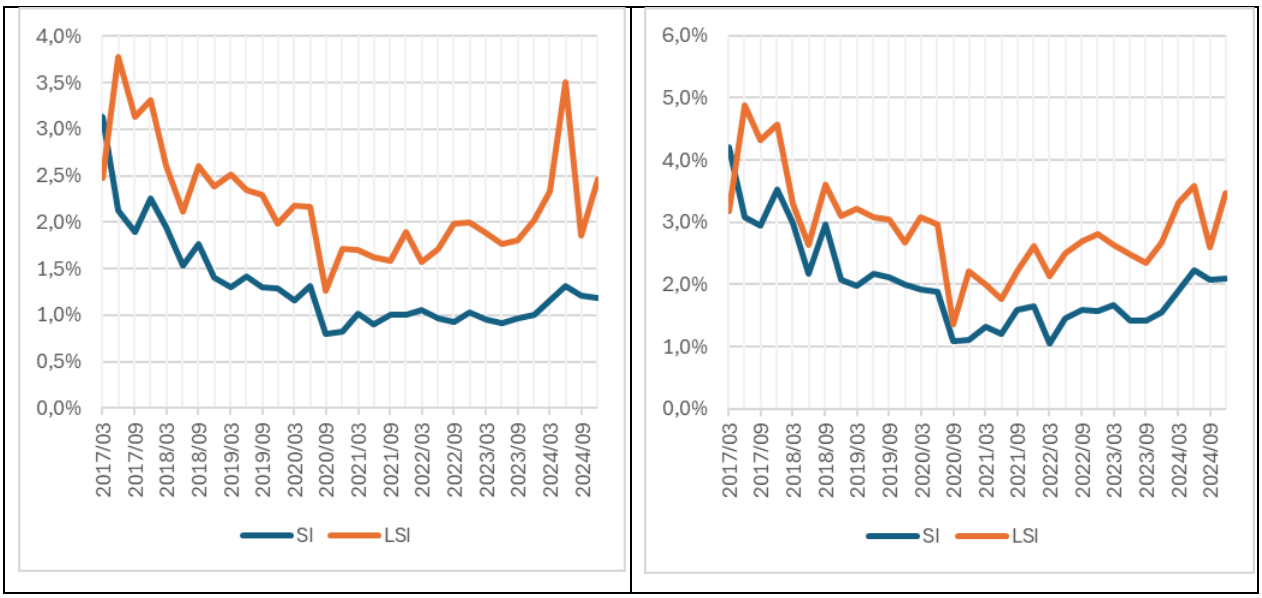
Variable	N	Mean	SD	Min	P5	Median	P95	Max
LSI dummy	2.592.014	0,14	0,35	0,00	0,00	0,00	1,00	1,00
Default dummy	2.592.014	0,01	0,11	0,00	0,00	0,00	0,00	1,00
Firms characteristics								
Liquidity to Assets	2.592.014	0,12	0,14	0,00	0,00	0,07	0,43	0,65
Turnover to Assets	2.592.014	0,99	0,72	0,02	0,06	0,89	2,35	3,77
Gross Oper. Income to Assets	2.592.014	0,08	0,10	-0,24	- 0,06	0,07	0,26	0,42
Financial Debt to Turnover	2.592.014	0,83	2,45	0,00	0,00	0,21	3,67	18,01
Leverage	2.592.014	0,41	0,35	0,00	0,00	0,42	0,94	1,39
Loans characteristics								
Original Maturity	2.592.014	7,29	5,01	0,00	1,04	6,01	17,08	84,29
Residual Maturity	2.592.014	4,53	3,61	0,00	0,36	3,92	11,17	79,05
Loan Amount (Log)	2.592.014	11,50	1,39	9,21	9,70	11,34	14,02	22,38
Spread	2.592.014	2,05	1,34	-4,98	0,39	1,79	4,54	22,58
Variable Rate dummy	2.592.014	0,51	0,50	0,00	0,00	1,00	1,00	1,00
Collateral dummy	2.592.014	0,89	0,31	0,00	0,00	1,00	1,00	1,00
Bank characteristics								
Cost to Income	2.592.014	0,67	0,14	0,41	0,44	0,65	0,94	1,08
Total Assets (Billions €)	2.592.014	241,1	269,1	0,17	1,50	128,9	774,2	774,2
Loans to Assets	2.592.014	0,57	0,06	0,19	0,47	0,58	0,67	0,97
Diversification index	2.592.014	0,49	0,12	-0,01	0,35	0,47	0,71	1,58
CET 1 Ratio	2.592.014	0,17	0,06	0,08	0,12	0,16	0,26	1,24
NPL Ratio	2.592.014	0,04	0,02	0,00	0,02	0,04	0,08	0,27
Coverage Ratio	2.592.014	0,54	0,10	0,01	0,43	0,51	0,76	1,00
NFC Share	2.592.014	0,44	0,09	0,00	0,32	0,43	0,57	0,91

Note: Diversification index is defined as the ratio of net interest income to total operating income. All variables are *winsorized* at 2nd percentile.

Figure 1 – Default rate by type of intermediary

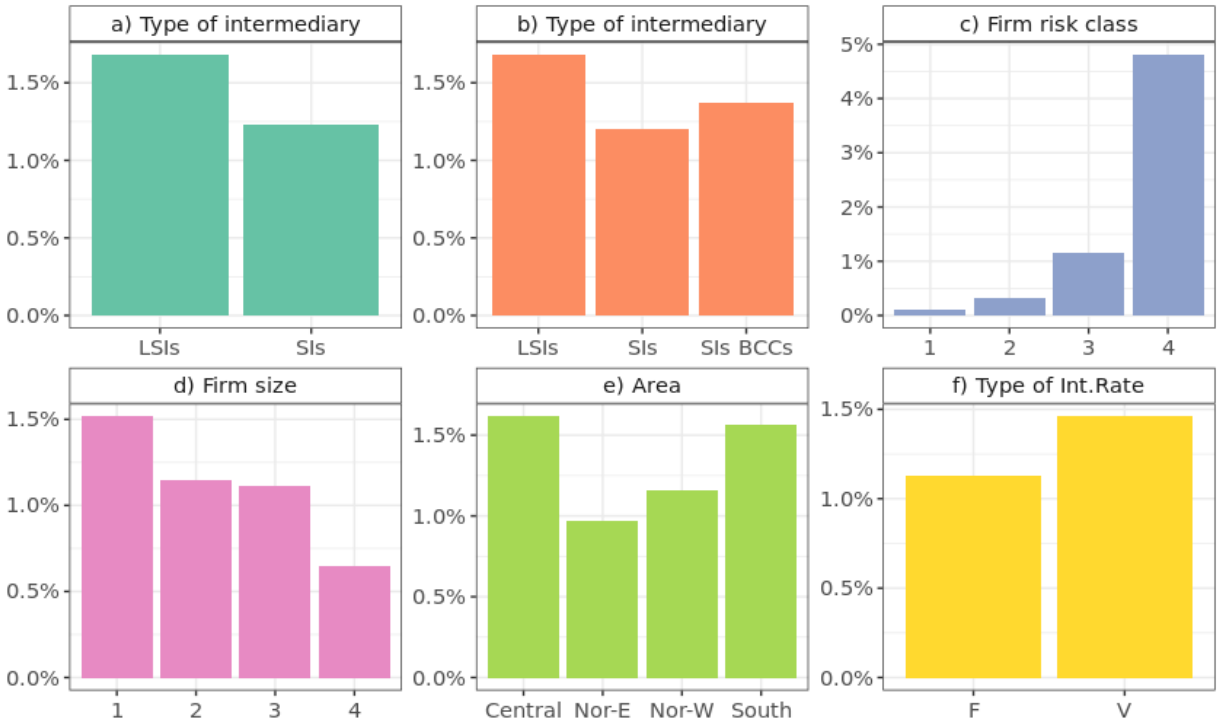
Panel A – Total

Panel B – NFC only



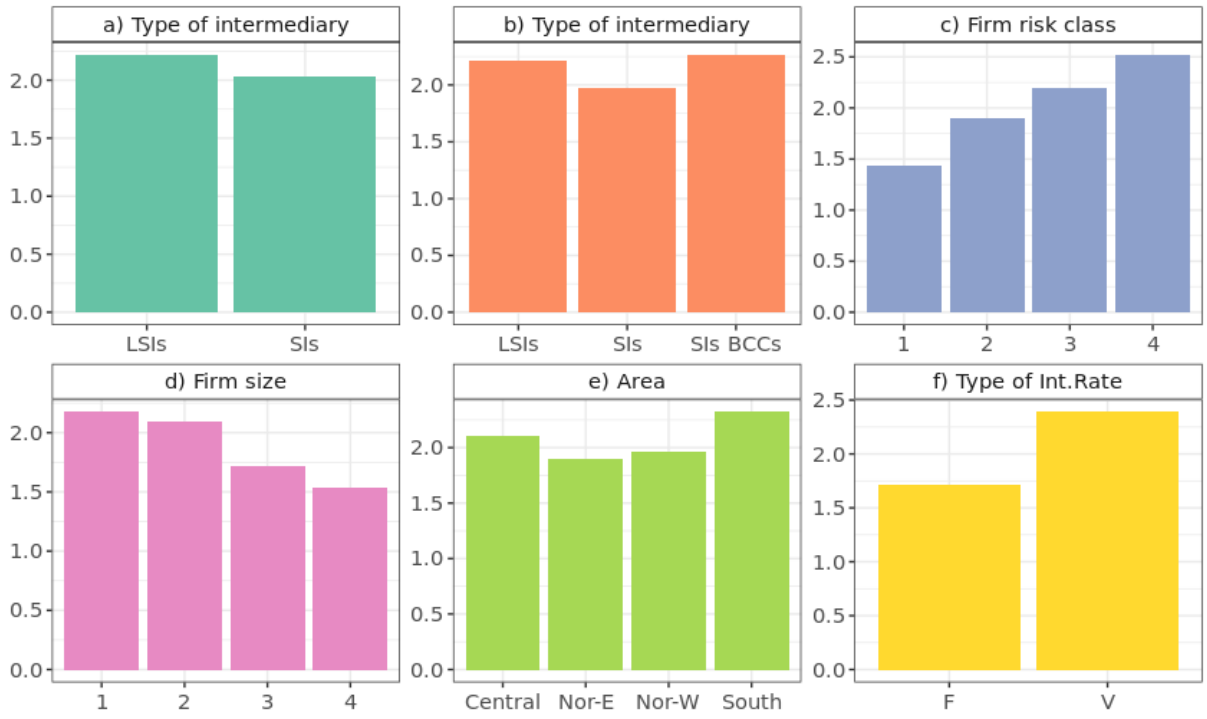
Source: Credit Register.
Note: The default rate is calculated as the ratio of new non-performing loans to performing loans in the previous quarter, annualized and seasonally adjusted.

Figure 2 – Average default rate



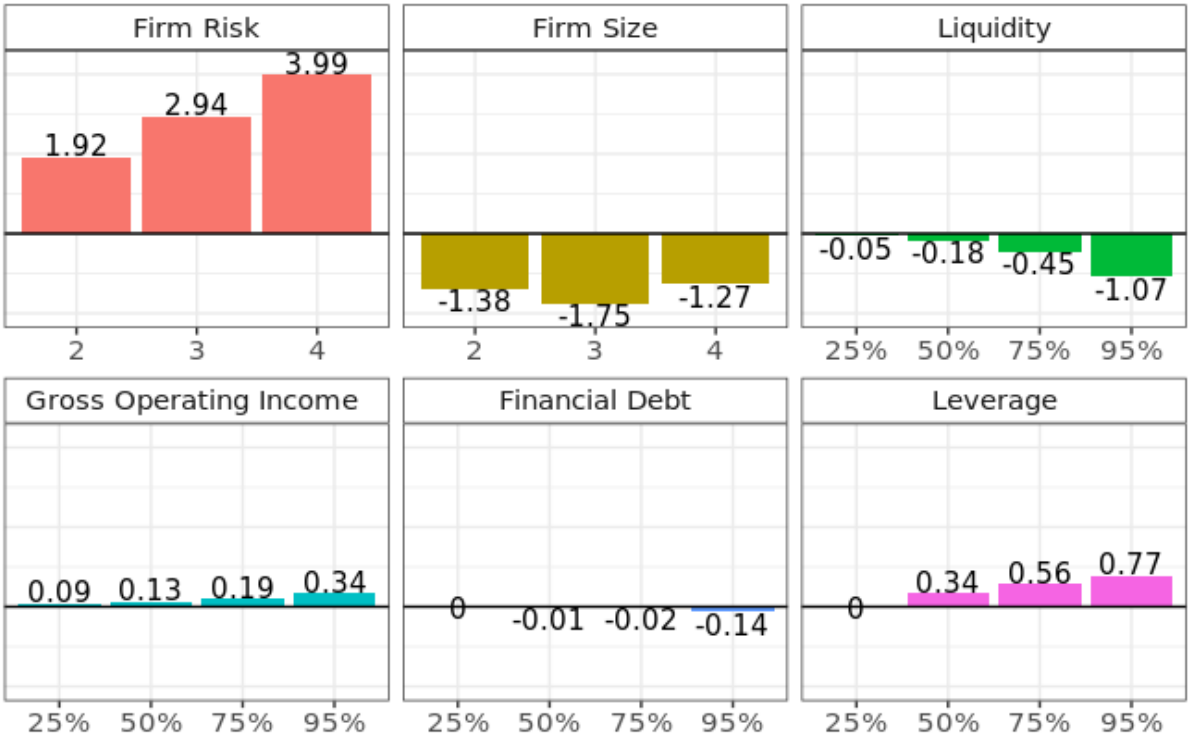
Source: Based on AnaCredit data.
Note: Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 3 – Average *spread*



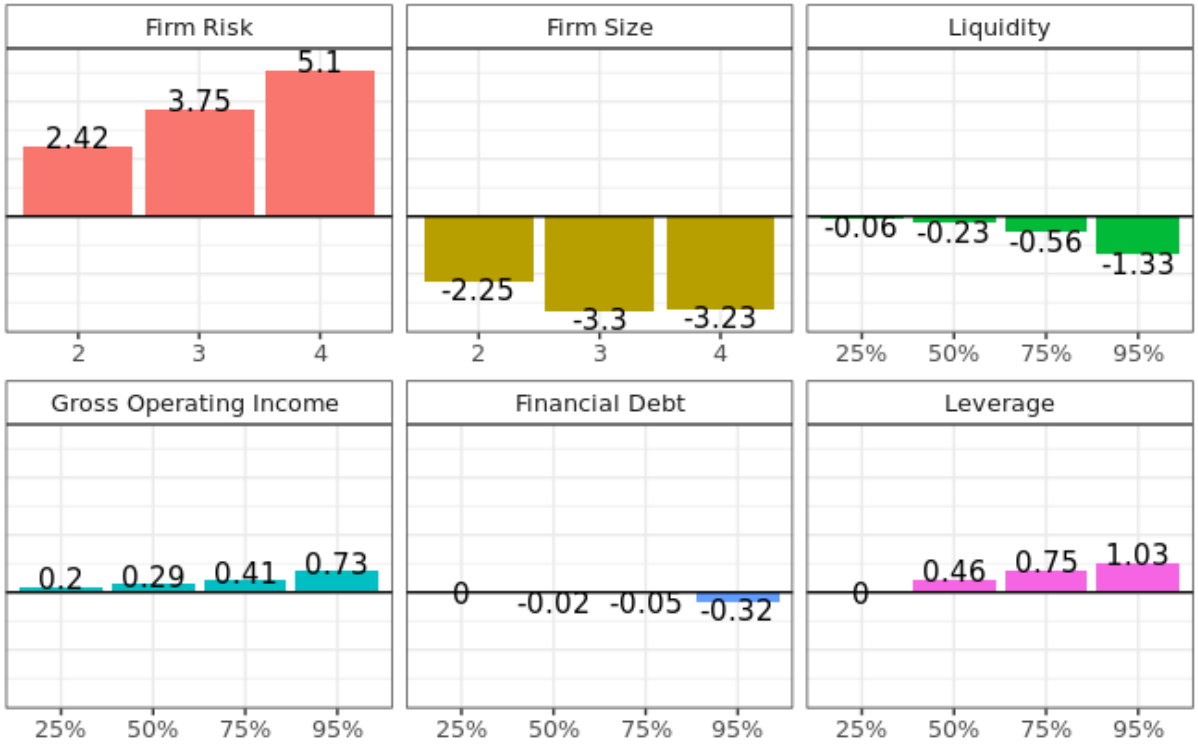
Source: Based on AnaCredit data.
Note: Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 4 - Average Marginal Effects for Model (1) – Y = LSI indicator



Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

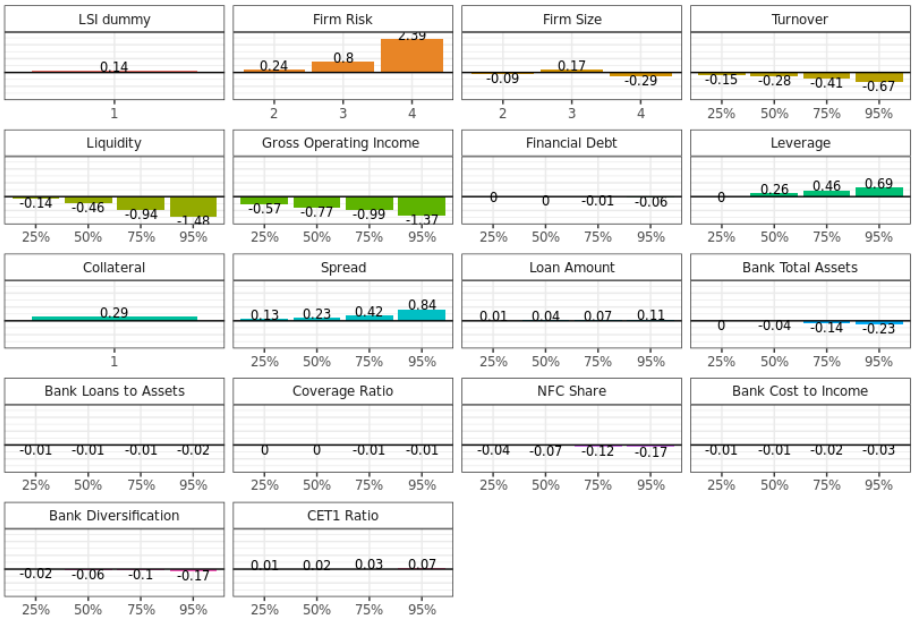
Figure 5 – Average Marginal Effects for Model (1), excluded SIs BCCs – Y = LSI indicator



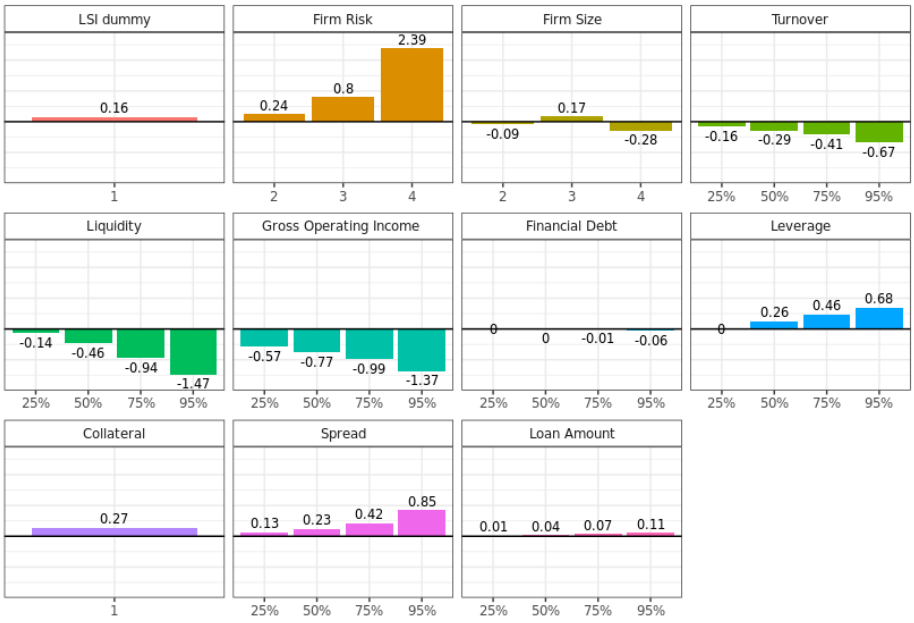
Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 6 – Average Marginal Effects for Model (2) – Y = *default* indicator

Panel A – Including intermediaries' characteristics



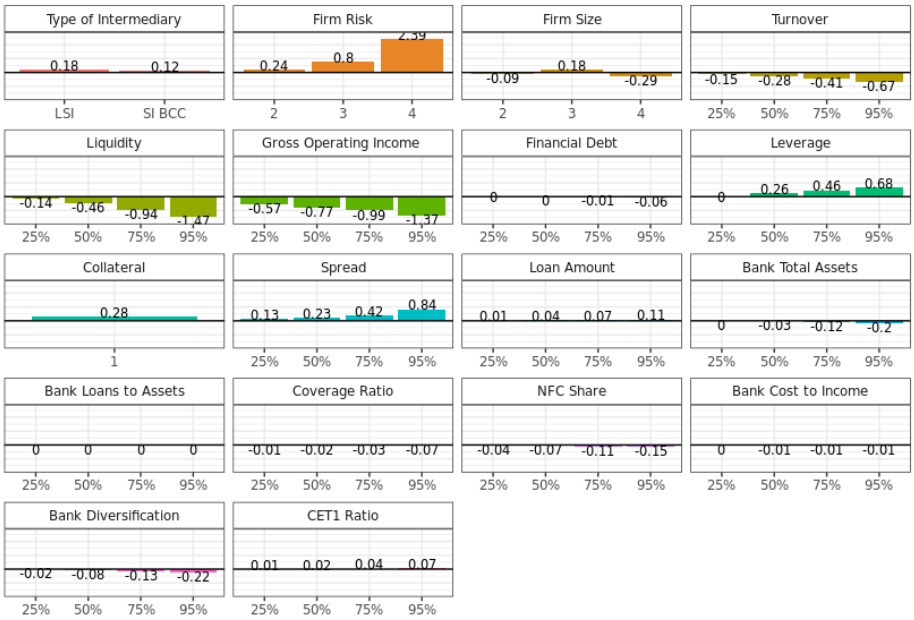
Panel B – Excluding intermediaries' characteristics



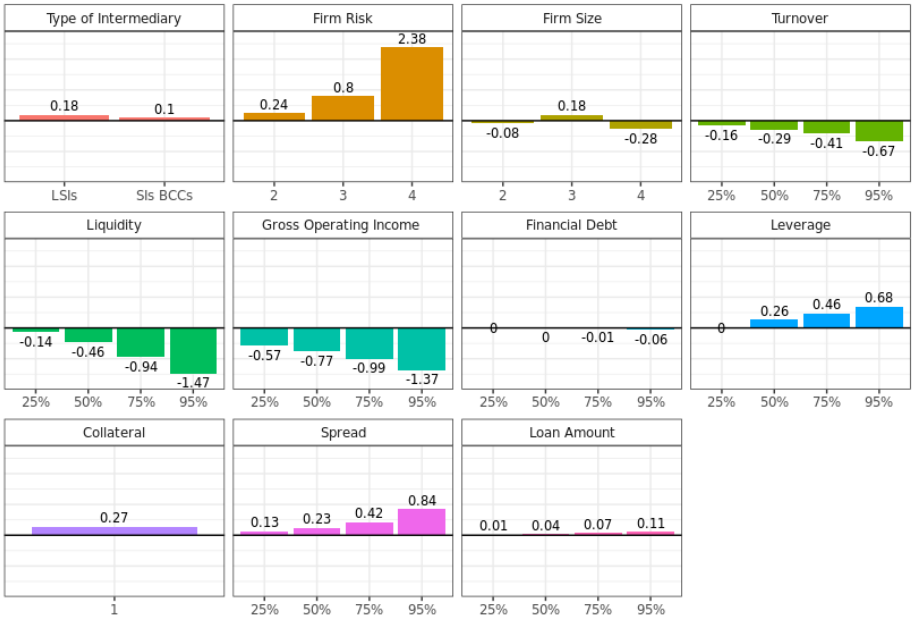
Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects, along with controls for both the year of origination and whether the loan was subject to a moratorium. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 7 – Average Marginal Effects for Model (2) – Y = *default* indicator

Panel A – Including intermediaries' characteristics



Panel B – Excluding intermediaries' characteristics



Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects, along with controls for both the year of origination and whether the loan was subject to a moratorium. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 8 – Average Marginal Effects for Model (3) – Y = *spread*

Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects, along with controls for both the year of origination and whether the loan was subject to a moratorium. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.

Figure 9 – Average Marginal Effects for Model (3) – Y = *spread*

Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects, along with controls for both the year of origination and whether the loan was subject to a moratorium. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms..

Annex – Initial information service

Initial information service (IIS) from Italian Credit Register allows intermediaries to request information on clients when they formally receive a credit application from a new borrower.[12] It can be assumed that each inquiry made by an intermediary regarding a firm is associated with a loan application submitted by the firm to the intermediary. Although it is not possible to distinguish between applications that were withdrawn and those that were explicitly rejected, some information can still be inferred regarding successful applications.

To ensure the robustness of this analysis, several data selection criteria are applied. First, firms with multiple inquiries from different banks within the same month are excluded to avoid misclassifying as rejections those loan applications that did not result in credit due to the borrower's decision rather than the intermediary's[13]. Second, for each bank-firm pair, only the final inquiry in a sequence is retained, defined as the last request after which no further inquiries occur within the subsequent three months. Third, anomalous spikes in inquiries at the bank-month level are identified and removed to mitigate the impact of irregular reporting or data inconsistencies. As in the previous dataset, specialized intermediaries and firms not included in the Cerved balance sheet database are excluded from the analysis.

Over the period considered, which spans from 2018 to 2024, this results in a dataset containing around 1 million applications (Figure A1). Following standard practice in the literature, a binary outcome (approved or rejected) is assigned to each credit application. An *approval* indicator is defined and takes the value 1 if, within the three month-period following the submission of an application, the Credit Register records the activation of a new credit line between the applicant firm and the intermediary that initiated the IIS. In the absence of a new credit line within the specified time frame, the indicator takes the value 0. As reported in the main text, average approval rate is 24.1 per cent for LSIs and 19.2 for SIs (Figure A2, Panel A).

However, some notes of caution must be considered: i) the Credit Register does not report credit exposures below the threshold of 30,000 euros, consequently loans approved for amounts below this threshold are not captured in the data; ii) banks may approve or reject loan applications without

[12] This service is for the credit and financial intermediaries that participate in the Credit Register. After it receives information on the loans granted by the participating intermediaries to individual customers, Banca d'Italia aggregates the data for each borrower and calculates their total debt exposure to the credit and financial system. This is called the *global risk position* and does not include details of individual financial intermediaries. With the *initial information service*, the intermediaries participating in the Credit Register may ask to know the global risk position of potential new customers, for a fee, with a maximum look-back period of 36 months. The service can only be used for purposes related to activities involving the assumption of credit risk.

[13] Approximately 4 per cent of the original observations were discarded.

consulting the IIS, implying that some credit decisions might not be reflected in the dataset; iii) riskier firms display a higher share of applications submitted to LSIs compared with safer firms (Figure A3, Panel A), pointing to a potential self-selection bias.

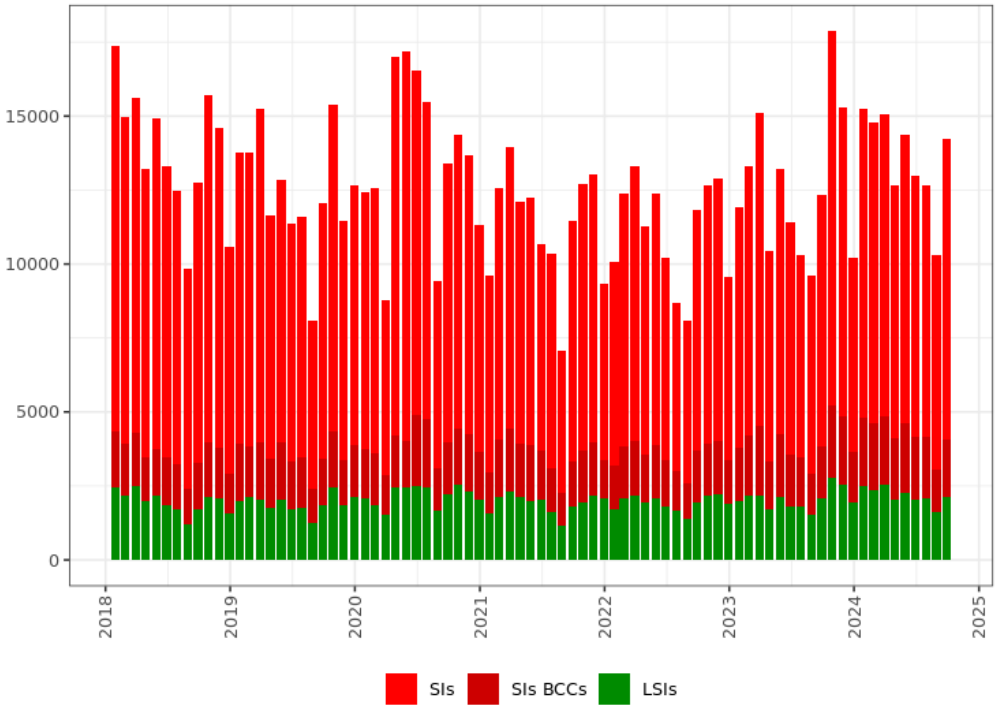
To investigate potential disparities in credit acceptance behavior between LSIs and SIs, the estimation of a logistic regression model is proposed:

$$log\left(\frac{P(approval_{i,b,t}=1)}{P(approval_{i,b,t}=0)}\right) = \beta_0 + \beta_1 LSI_{i,b,t} + \beta' X_{i,t-1}^{firm} + \theta_t + \xi_s + \psi_p + \varepsilon_{i,b,t} \quad \text{(A1)}$$

In equation (A1), the explanatory variables include the same firm-level characteristics $X_{i,t-1}^{firm}$ and the $LSI_{i,b,t}$ indicator already used in equations (1)-(3), as introduced in Section 4 of the main text. As shown in Figure A4, loan applications submitted to LSIs are 3.9 percentage points more likely to be accepted than those submitted to SIs, for firms with comparable characteristics. While acknowledging the limitations discussed, this finding suggests that, on average, LSIs tend to be more willing to approve loan applications compared to SIs.

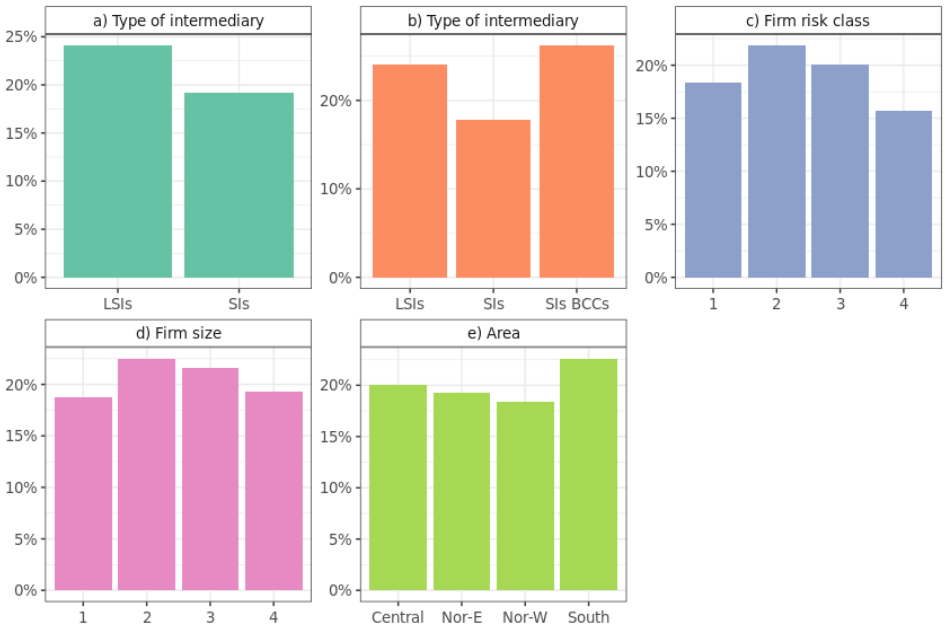
Annex Figures

Figure A1 - Number of inquiries in the sample by type of intermediary



Source: Based on Credit Register.

Figure A2 - Average approval rate

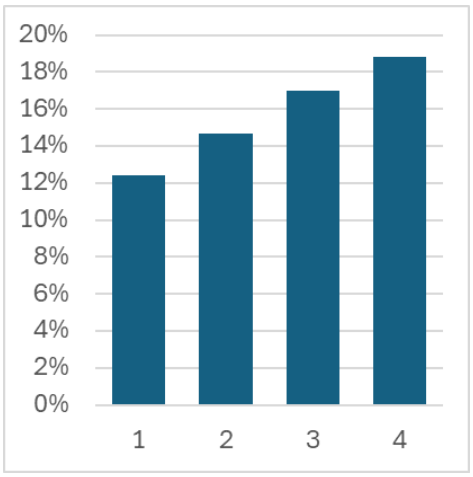


Source: Based on Credit Register.

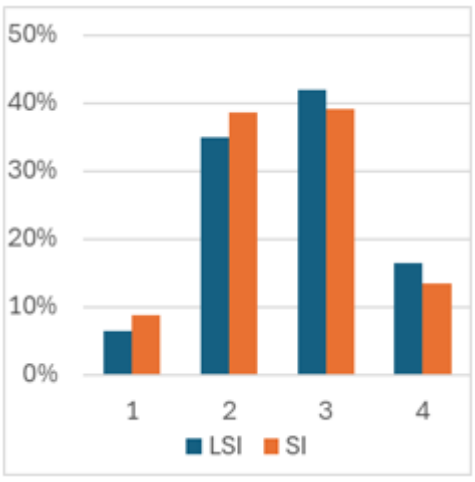
Note: Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms. A loan is considered as approved if, within the three months following the application, the Credit Register records the activation of a new credit line. Risk indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level.

Figure A3

Panel A – Share of LSI inquiries by risk class



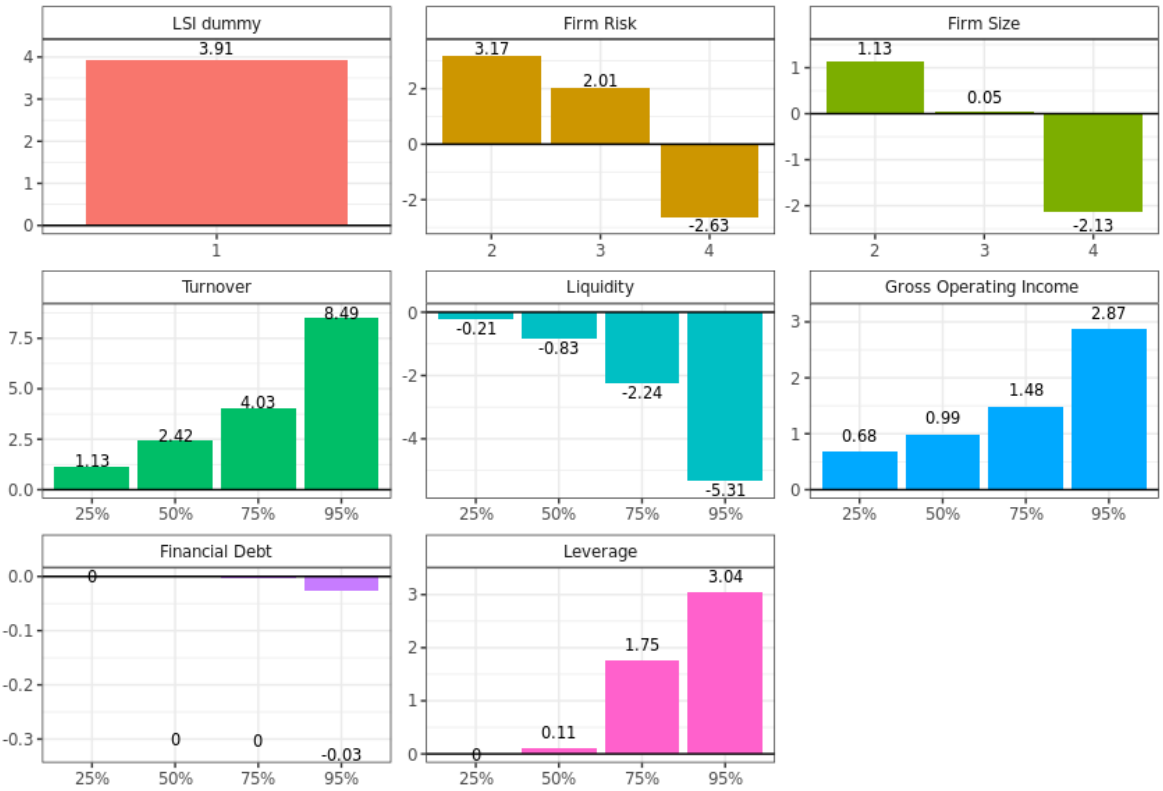
Panel B – Distribution of inquiries



Source: Based on Credit Register.

Note: The Risk indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Panel A shows the share of applications LSI over the total number of applications of each risk class. Panel B shows the distribution of the applications among each risk classes, by group of intermediaries.

Figure A4 – Average Marginal Effects for Model (A1) – Y = *approval* indicator



Note: Average Marginal Effects (AMEs) represent the average of the marginal effects calculated for each observation in a sample. In other words, they show the average effect of a change in an independent variable on the dependent variable, taking into account the specific characteristics of each observation. For quantitative variables, base levels are set at the fifth percentile of their empirical distribution and AMEs are computed and reported at selected quantiles of the regressors. All AMEs shown in the figure are associated to statistically significant coefficients ($p < 0.01$). The specification includes time, geographic, and sector fixed effects. Risk class indicator is provided by Cebi-Cerved; (1) is the lowest level and (4) is the highest level. Firm size classes are defined according to the EU Commission's definition of micro (1), small (2), medium (3) and large (4) firms.