



## **WHICH BANKS WERE MORE EFFECTIVE IN SUPPORTING CREDIT SUPPLY DURING THE PANDEMIC?**

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*This note investigates which bank characteristics explain the observed heterogeneity in bank credit supply to non-financial corporations (NFCs) during the pandemic, focusing on both balance-sheet and organizational factors. According to the findings of the empirical analysis, bank credit developments were mostly unrelated to bank capital and liquidity buffers during the central months of the pandemic outbreak. The analysis confirms, instead, the importance of organizational indicators: intermediaries that rely more on digitalized processes for the provision of credit were able to expand lending faster, especially during the lockdown.*

### **1. Introduction and main results**

The outbreak of the COVID-19 pandemic posed major challenges to the real economy and the financial system worldwide. Once the impact of the adverse shock became apparent, many feared that a credit crunch would trigger a negative spiral, leading to a large wave of non-financial corporation (NFC) defaults. There were concerns that banks' inability or unwillingness to supply credit during a surge in liquidity demand would exacerbate the effects of the pandemic. Against this background, Governments in many countries implemented several policy measures to support credit provision, such as debt moratoria and public guarantees.<sup>2</sup> At the same time, the European Banking Authority (EBA), the European Central Bank (ECB), and the National Competent Authorities (NCAs) eased capital and liquidity requirements, and enacted other measures related to asset quality deterioration and the management of non-performing loans (NPLs).<sup>3</sup> In Italy, aggregate data show that the flow of lending to NFCs increased rapidly from March 2020 (Figure 1). The expansion of lending reflects the medium and long-term component, which benefits from the COVID-19 public

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<sup>2</sup> In the case of Italy, debt moratoria for SMEs were introduced by Decree Law 18/2020 ('Cure Italy' decree) and measures related to new state-backed loans (via the Central Guarantee Fund or the public agency SACE) by Decree Law 23/2020 ('Liquidity Decree').

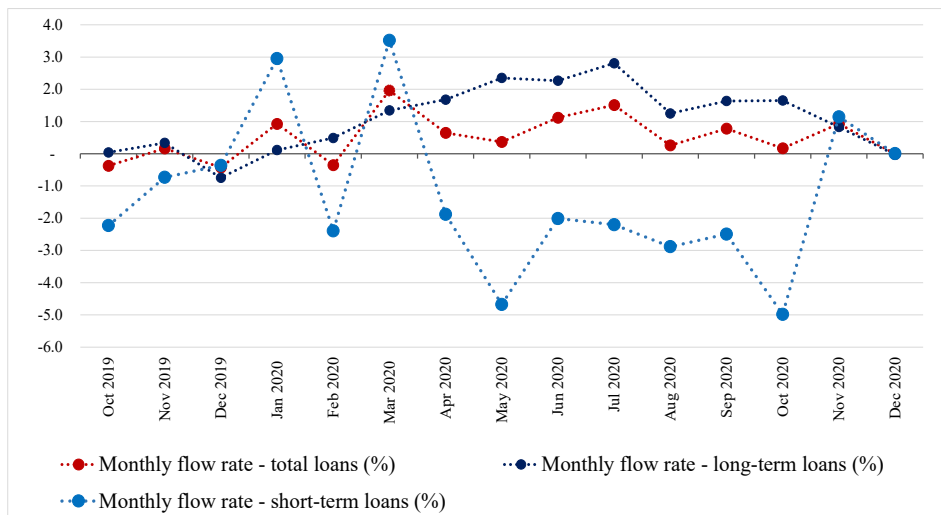
<sup>3</sup> Banks were allowed to operate temporarily below the level of the Pillar 2 Guidance (P2G), to draw down their liquidity buffers and to exploit the flexibility embedded in accounting and prudential standards when measuring credit deterioration and classifying assets. The Bank of Italy extended these measures to less significant banks and to non-bank intermediaries.

guarantees.<sup>4</sup> At end-2020, guaranteed loans accounted for about 18 per cent of loans to firms and this increase goes a long way to explaining the surge in bank loans observed during the pandemic.

Credit growth was heterogeneous among banks. Loans increased faster for larger institutions, especially the banking groups identified as Significant Institutions (SIs) by the Single Supervisory Mechanism (SSM; Figure 2).

**Figure 1 - Monthly flow of lending to firms by loan type**

(Per cent)

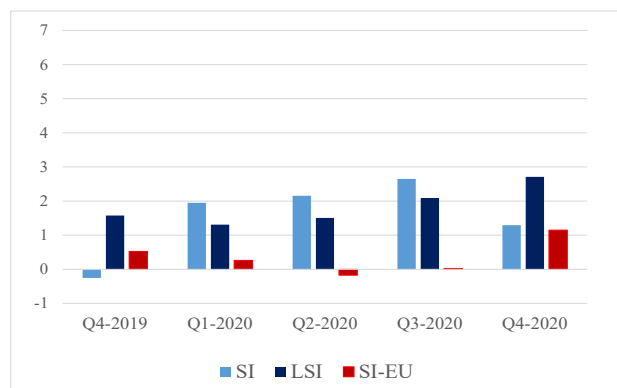


Source: Supervisory Reports, Bank of Italy. Note: we calculate the indicator as the net flow of lending in a month over the stock of loans at the end of the previous month.

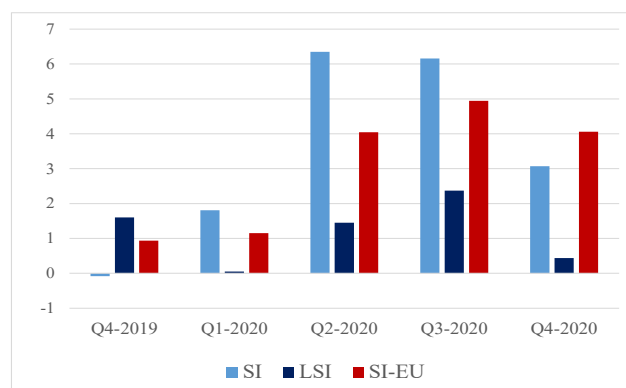
**Figure 2 - The net flow of lending to firms by bank category**

(Per cent)

a) Total loans



b) Long-term loans



Source: Supervisory reports, Bank of Italy. Note: the bank categories include those identified as Significant Institutions (SIs, including the two cooperative banking groups) and Less Significant Institutions (LSIs, including other cooperative banks), and subsidiaries of foreign significant banking groups (SI-EU) according to the SSM definition. We calculate the indicator as the quarterly net flow of lending over the stock of loans at the end of the previous quarter.

<sup>4</sup> Medium and long-term loans are those whose maturity is greater than one year. The volume of short-term loans spiked in March partly because of the withdrawal of funds by firms on existing credit lines. Short-term credit started to contract once the economic downturn began and procedures to access long-term loans with public guarantees became fully effective.

This note investigates which bank characteristics correlate with credit supply to NFCs during the pandemic. In particular, we consider two sets of factors: balance-sheet characteristics, which usually have an impact on credit growth (such as liquidity, capitalization, funding structures and the share of loans to NFCs);<sup>5</sup> and organizational variables, represented by the use of technology to interact with potential applicants for new loans and the adoption of advanced methods to assess the credit risk of prospective borrowers.

We expect that banks holding substantial liquidity and capital at the onset of the pandemic would be better able to support lending as opposed to banks with fewer liquid assets or less capital. Although supervisors adopted relief measures, stigma effects could have prevented banks from increasing lending.<sup>6</sup> We also consider the level of reliance on stable forms of funding such as deposits to customers and the share of loans to NFCs over total loans in order to capture two important features of the business model: the existence of well-established bank-firm relationships (in terms of deposits) and specialization in lending to NFCs.

During the early months of the COVID-19 outbreak the country was locked down, significantly reducing the ability of banks to serve their clients. Intermediaries that could largely rely on digital processes in lending should have been better able to handle demand for loans efficiently and swiftly, even with a substantial share of staff working remotely. Although most banks do not issue loans entirely online, banks with more intensive use of technology should have been better able to exchange information with their clients and process applications collected at branches (Core and De Marco 2021).

The results of the analysis show that most bank balance-sheet variables did not significantly affect lending during the central months of the pandemic outbreak, in particular from April 2020. This may support the interpretation that policy measures introducing flexibility in regulatory requirements were effective in supporting the surge in liquidity demand by firms. As far as organizational efficiency in lending processes goes, our results indicate that intermediaries providing online lending services and employing advanced scoring methods were better able to adapt to the new operating environment. We also find that physical branches were important in allocating credit, since their presence in a given province contributed positively to credit growth in the second quarter of 2020. As observed in other works (Core and De Marco, 2021 and Branzoli et al., 2021), this latter evidence is not in contrast with the important role of technology in credit supply during the lockdown and the subsequent months. Indeed, branches could be capturing the intensity of pre-existing lending relationships and the footprint of the bank in local lending markets.

## 2. Empirical analysis

The empirical analysis is based on a set of regression models showing the net flow of loans to NFCs by bank  $i$  in province  $p$  in the period  $d$  relative to a set of bank characteristics.<sup>7</sup> These include balance-sheet factors, size, organizational variables and some bank-province control variables (the market share of a given bank in a province and the number of branches in that province, scaled by loans).<sup>8</sup>

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<sup>5</sup>We select bank characteristics among those identified in the literature as the main factors influencing credit developments (see, among others, Li et al., 2020, Cornett et al., 2011).

<sup>6</sup>See the FAQs on ECB supervisory measures in response to the coronavirus, [https://www.bankingsupervision.europa.eu/press/publications/html/ssm.faq\\_ECB\\_supervisory\\_measures\\_in\\_reaction\\_to\\_the\\_coronavirus~8a631697a4.en.html](https://www.bankingsupervision.europa.eu/press/publications/html/ssm.faq_ECB_supervisory_measures_in_reaction_to_the_coronavirus~8a631697a4.en.html)

<sup>7</sup>The net flow of loans is the ratio of the net lending flow to NFCs over a time interval and the stock of loans at the beginning of the period. The data sources are Supervisory Reports, the Regional Bank Lending Survey (RBLs) for organizational indicators and a survey carried out by Bank of Italy for guaranteed loans under the ‘Liquidity Decree’.

<sup>8</sup>The regressions also include province-fixed effects referring to the province where the loans were granted. Thanks to data on bank lending by province we can control for differences in local demand conditions with province-fixed effects

The various specifications refer to different assumptions about the category of loans (either total or long-term loans) and the size of borrowing firms (either small or medium-to-large).

An initial analysis investigates the impact of bank variables – as of December 2019 (pre-COVID period) – on credit supply to NFCs in Q2 2020, the period including (most of) the first lockdown and the implementation of the first relief measures.

For small-sized NFCs (Table 1A) the results show an overall low significance of balance-sheet variables. The leverage and liquidity ratios do not have statistically significant coefficients, supporting the view that there were no constraints on bank lending due to regulatory limits. A low significant and negative impact on lending is related to the loan-to-deposit ratio, suggesting that banks with a stronger deposit-to-customer base in the pre-crisis period (December 2019) were better able to increase loans.

Both the branch network and organizational indicators, including either the provision of online lending services and advanced methods for credit assessment, were instead important drivers of lending. The coefficient of branches over loans is significant and positive (0.06 for total loans and about 0.1 for long-term loans): banks increased lending in the local markets where they were more present and had established relations with the local firms. As to online and credit scoring variables, they can be considered good proxies for the extensive and efficient use of technology to support credit supply. The results suggest that banks that rely more on digitalized organizational processes for lending are the ones that increased lending to small-sized firms during the pandemic the most, as they were better equipped to support their clients and process applications collected at branches.

The findings are similar for medium-to-large NFCs; however, the relations are weaker than in the case of small-sized firms (Table 2A).

As a further test, we replicate the analysis outlined above, considering as a dependent variable the flow of new guaranteed loans to small and medium-to-large firms issued under the provisions of the ‘Liquidity Law’ (Legislative Decree 232020) in Q2 2020.<sup>9</sup> Overall, the results confirm our main findings for total and long-term loans. In the specific case of guaranteed loans, a significant bank variable is the share of loans to small-sized firms. This suggests that banks that were more specialized in lending to small-sized firms granted more new guaranteed loans to them during the early months of pandemic. Moreover, there is a positive effect of the average number of branches in the provinces where the bank operates (in terms of total loans) on lending.

A second analysis investigates whether bank characteristics have different effects over time.<sup>10</sup> We test for differences in the sensitivity of lending to the variables of interest during the different phases of the COVID-19 pandemic, proxied by the quarters from Q4 2019 to Q4 2020.<sup>11</sup> We calculate the

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(e.g. Bonaccorsi di Patti et al., 2005). We consider only the cases where the share of loans in a given province granted by a bank is greater than 0. We mainly focus on long-term loans.

<sup>9</sup> The regression is estimated with bank-level data due to the unavailability of a bank-province breakdown.

<sup>10</sup> We follow a similar approach to the one proposed by Li et al. (2020). The lending flow indicator refers to bank  $i$  in province  $p$  in the quarter  $q$ . In addition to the regressors used in the Q2 2020 analysis, we include dummy variables  $d_q$  for each quarter from Q4 2019 ( $q=0$ ) to Q4 2020 ( $q=4$ ) and their interactions with bank variables. The financial indicators refer to the end of the previous quarter for the different sub-periods.

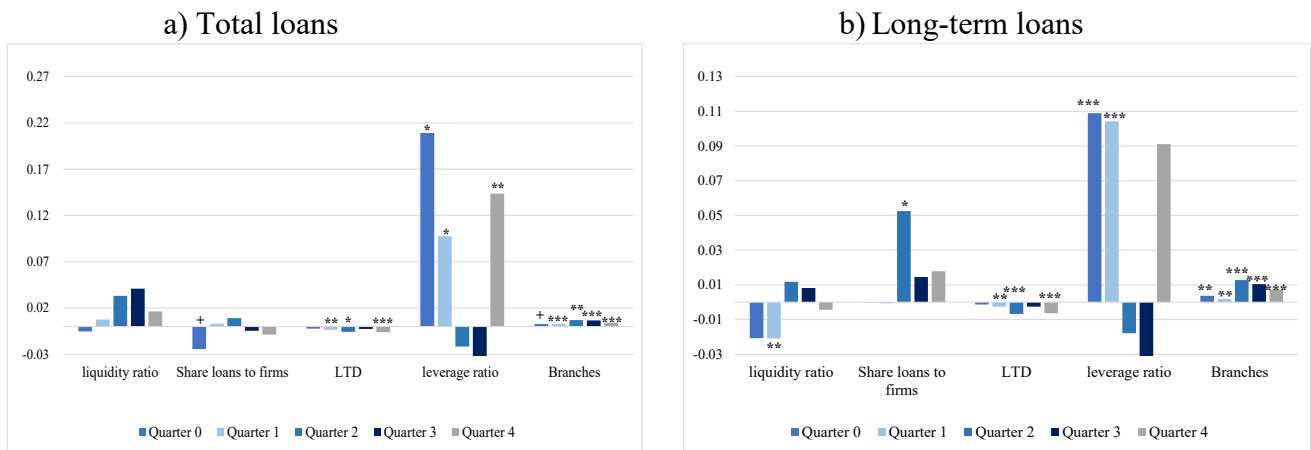
<sup>11</sup> The quarters are a faithful representation of the different phases in terms of the implementation of measures, credit developments and the pandemic spread (Figure A.1 in the annex): 1) the last quarter of 2019 is defined as the pre-COVID-19 period; 2) in Q1 2020 COVID-19 struck and spread rapidly throughout the country. Most measures to support the economy were approved in March but only became fully effective in April. Credit growth was concentrated in short-term loans; 3) Q2 2020 was characterized by an extended lockdown and intensive activation of different measures. Credit growth was concentrated in long-term loans; 4) Q3 2020 is the period between the two pandemic waves; 5) Q4 2020 includes the second pandemic wave in Italy. Moreover, most of the bank variables are shown on a quarterly basis.

marginal effects of each variable, representing the overall effects of it on the net flow of lending over each quarter and indicating how much the dependent variable changes with respect to a unit change of a given regressor.<sup>12</sup>

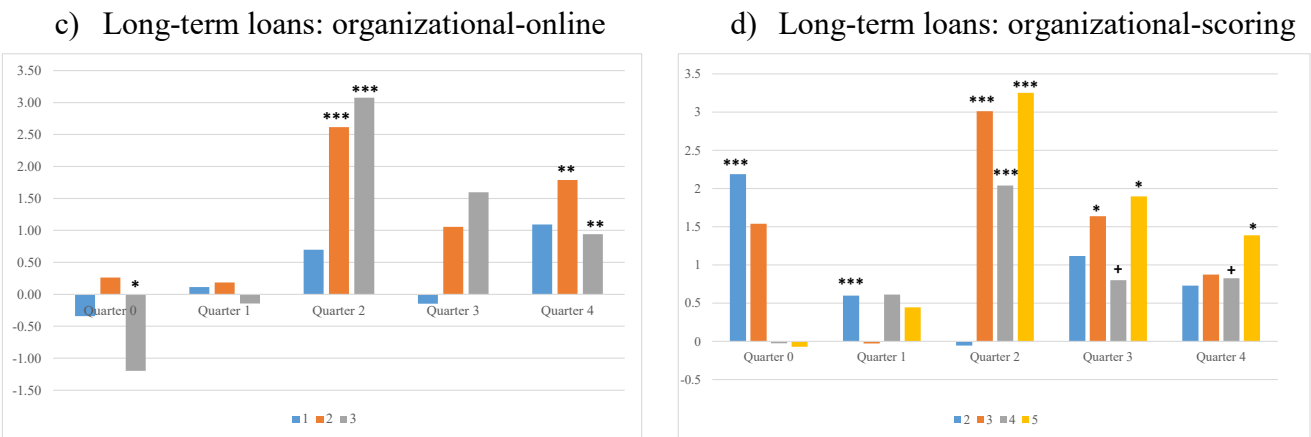
Regarding loans to small-sized firms, the effect of some bank variables on lending can vary over quarters (Figure 3). This is evident for the leverage ratio<sup>13</sup> (defined as CET1 over total assets, panels a and b). This variable is statistically significant in the last quarter of 2019 (pre-COVID-19 period) and in the first quarter of 2020 (including at the beginning of the pandemic outbreak) and becomes not statistically significant during the second quarter, after the measures enacted by the Government and supervisory authorities became fully effective.

**Figure 3 - Marginal effect of main variables over quarters - loans to small-sized firms**

Balance-sheet indicators and branch network



Organizational variables



Note: Quarters are from Q4 2019 (0) to Q4 2020 (4). Panels c) and d) refer to organizational variables: *organizational-online* (panel c) counts the number of services where the bank uses online procedure (from 0 to 3), *organizational-scoring* (panel d) represents the importance of scoring procedures for a bank, from 1 (no importance) to 5 (maximum importance). Marginal effects for categorical variables is the discrete change from the base level (0 and 1, respectively). Standard errors (over each bar): +  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

The leverage ratio remains not statistically significant in the third quarter as well and, interestingly, becomes statistically significant again in the final months of 2020. This finding could reflect bank

<sup>12</sup> In the case of a categorical variable, the marginal effect is the discrete change from the base level.

<sup>13</sup> The capital-based indicator used in this analysis is the leverage ratio, as we are interested in the effect of capital on lending, without taking into account the possible effect of policy measures on risk-weighted assets. As a robustness check, we estimate our regressions including the CET1 ratio (defined as CET 1 over RWAs) instead of the leverage ratio; the results are similar, but the effect of the variable on lending is weaker.

policy decisions on capital management at the end of the year or could signal that banks were becoming more cautious because they expected credit risk to increase in the near future and some support measures to expire. As to the other bank characteristics, the loan-to-deposit ratio (LTD, panels a and b) has a (low) negative and significant coefficient over different quarters, suggesting that banks with a stronger deposit-to-customer base were better able to increase loans, while the other variables are not statistically significant.

As regards organizational variables, their impact on lending vary over time (Figure 3, panels c and d). The two indicators are not significantly related to lending growth in Q4 2019 and Q1 2020, but turn significant, with a positive effect, in Q2 2020. This result suggests that banks which had already invested in digital processes did not have a particular advantage before the pandemic, but were instead better able to serve their clients when mobility restrictions were imposed. These variables remain relevant in the following quarters, even though their effect is smaller than the one observed in Q2 2020.

The results for medium-to-large firms are similar to those for small-sized NFCs, especially for long-term loans. Also in this case there is no significant correlation between bank characteristics and credit supply across the different quarters of 2020. Notably, the effects of the organizational variables are smaller. Overall, the use of technology seems to have had a larger impact in the case of loans to small-sized firms, as these are the most involved in relationship lending with intermediaries and therefore more negatively affected by restrictions on physical interactions at branches during the lockdown.

### 3. Conclusions

Our empirical analysis highlights that the growth of lending by banks during the pandemic was largely uncorrelated with variables typically influencing bank credit supply (Cornett et al., 2011, Li et al., 2020). This finding can be a signal that policy measures by Governments and European regulatory authorities introducing state-backed guarantees and flexibility in capital and liquidity requirements, respectively, were effective in supporting the provision of credit by banks during times of exceptional liquidity demand by firms. The effectiveness of these policies likely benefited from the substantial improvement of capital and liquidity positions by banks as a result of the post 2007-08 crisis regulatory reforms.

Another important finding of our analysis is that intermediaries providing online lending services and employing advanced scoring methods were better able to adapt their activities to the new operating environment ushered in by the pandemic outbreak. Indeed, banks that had already invested in digital processes served their customers more efficiently than others during the lockdown and when restrictions to physical interaction were in place.

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Annex

Table 1A - Results of cross-section regression model for loans to small sized NFCs

	Total	Long-term	Long-term	Long-term
Liquidity ratio	0.017 (0.02)	0.007 (0.02)	0.015 (0.02)	0.020 (0.02)
Loan-to-deposit	-0.002** (0.00)	-0.002* (0.00)	-0.002** (0.00)	-0.002* (0.00)
Leverage	0.039 (0.04)	0.023 (0.05)	0.065 (0.06)	0.069 (0.04)
Share of small NFC loans	0.006 (0.01)	0.001 (0.01)	0.007 (0.01)	0.009 (0.01)
Market share	-0.220+ (0.13)	-0.006 (0.12)	0.004 (0.12)	0.121 (0.11)
Branches over loans	0.063*** (0.01)	0.099*** (0.01)	0.096*** (0.01)	0.089*** (0.01)
BCC	-1.040* (0.51)	-1.244* (0.54)	-0.973+ (0.50)	-1.992*** (0.47)
2.class (medium)	0.278 (0.33)	0.732* (0.28)	0.638* (0.28)	0.311 (0.33)
3.class (other large)	0.590 (0.66)	1.519* (0.67)	1.194+ (0.63)	1.519* (0.62)
4.class (top 5)	0.596 (0.55)	2.046*** (0.58)	1.425* (0.67)	1.573* (0.64)
1.org_online			0.356 (0.38)	
2.org_online			0.873+ (0.51)	
3.org_online			1.163+ (0.66)	
2.org_scoring				0.220 (1.15)
3.org_scoring				0.826 (0.54)
4.org_scoring				1.124*** (0.31)
5.org_scoring				2.031*** (0.48)
Constant	-0.483 (0.76)	-0.472 (0.76)	-1.217 (0.86)	-1.678* (0.69)
<i>N</i>	3794	3794	3794	3794
adj. <i>R</i> <sup>2</sup>	0.06	0.22	0.23	0.25
Error	Cluster (bank)	Cluster (bank)	Cluster (bank)	Cluster (bank)
FE province	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, +  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . BCC is a dummy equal to 1 if the intermediary is a cooperative bank, 0 otherwise. The variable class is a categorical variable for bank size, *org\_online* (from 0 to 3) is a categorical variable counting the number of services where the bank use online procedures, *org\_scoring* (from 1 to 5) is a categorical variable representing the relevance of scoring procedures for a bank.

Table 2A - Results of cross-section regression model for loans to medium-to-large NFCs

	Total	Long-term	Long-term	Long-term
Liquidity ratio	0.017 (0.02)	-0.008 (0.01)	-0.013 (0.01)	-0.004 (0.01)
Loan-to-deposit	-0.001 (0.00)	0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)
Leverage	0.030 (0.11)	-0.015 (0.05)	-0.036 (0.05)	0.000 (0.05)
Share of large NFC loans				
Market share	0.001 (0.02)	0.013* (0.00)	0.013* (0.01)	0.010+ (0.01)
Branches over loans	-0.158 (0.26)	0.303* (0.14)	0.288* (0.14)	0.322* (0.14)
BCC	-0.026 (0.02)	0.041*** (0.01)	0.043*** (0.01)	0.039*** (0.01)
2.class (medium)	-0.922+ (0.55)	-0.469 (0.44)	-0.530 (0.46)	-0.581 (0.47)
3.class (other large)	-0.134 (0.79)	0.468+ (0.27)	0.535+ (0.27)	0.353 (0.32)
4.class (top 5)	-0.115 (0.99)	0.945+ (0.52)	0.994+ (0.51)	0.933+ (0.49)
1.org_online	0.351 (0.81)	1.174* (0.48)	1.598* (0.70)	0.929 (0.63)
2.org_online			-0.314 (0.30)	
3.org_online			-0.144 (0.35)	
2.org_scoring			-0.907 (0.65)	
3.org_scoring				-0.391 (0.62)
4.org_scoring				0.149 (0.53)
5.org_scoring				0.275 (0.31)
Constant				0.519 (0.58)
<i>N</i>	5355	5355	5355	5355
adj. <i>R</i> <sup>2</sup>	0.00	0.06	0.07	0.07
Error	Cluster (bank)	Cluster (bank)	Cluster (bank)	Cluster (bank)
FE province	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, +  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . BCC is a dummy equal to 1 if the intermediary is a cooperative bank, 0 otherwise. The variable class is a categorical variable for bank size, *org\_online* (from 0 to 3) is a categorical variable counting the number of services where the bank use online procedures, *org\_scoring* (from 1 to 5) is a categorical variable representing the relevance of scoring procedures for a bank.

Figure A1 - COVID-19 pandemic facts

