Recovery lending and local banking: evidence from the Italian earthquake of 2012

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Abstract

This paper analyses the differences between local and commercial banks, focusing on credit supply in the aftermath of a natural disaster. Using the earthquake that hit Northern Italy in 2012 as exogenous shock, in the first part of the analysis, the study relies on a diff-in-diff approach. We show that cooperative banks, differently from commercial banks, do not interrupt the credit channel, hence supporting the economic recovery of the territory. To support these findings, we also perform panel estimation, using additional explanatory variables, such as: personal income, bank deposits, and bank branches. Results are coherent with the diff-in-diff approach, suggesting local banks increased credit supply (i.e., recovery lending) in the territories affected by the earthquake, while there is no evidence in this sense for commercial banks.

[1] The views and opinions expressed in this paper are those of the authors and do not necessarily reflect the views or positions of Federcasse.

1. Introduction and literature review

It is crucial, nowadays, to understand the reaction of the banking system to the exogenous shocks represented by natural disasters. There are numerous threats posed by natural disasters to the economy of a territory: unemployment might rise, companies might undergo severe damages and losses and, consequently the banking system might be stressed.

The economic literature has started addressing this question in the last years. Botzen et al. (2019) conducted a review of models and empirical studies on the economic impact of natural disasters. They found that worldwide, from Japan to the US, earthquakes, hurricanes, and tsunamis have caused more and more damages over the last few years, leading to an increase in economic losses. They identify direct and indirect economic effects of such events: the first ones are identified by the direct damage to assets and properties, whereas the second ones include the interruption of economic activities and the short-term and long-term economic losses. The authors conclude giving suggestions on how to mitigate disasters impact and lessons for policymakers as well as an agenda for future research.

In one study by the FED of New York, Blickle et al. (2021) exploited the FEMA database to investigate the effects of natural disasters on banks; they focused on the difference between local and more diversified banks, finding small or insignificant effects on banks performance and stability following natural disasters. These events are not sufficient to threaten bank solvency, not even local ones. In particular, the authors listed three possible factors that might increase banks' resilience: FEMA disaster aid; the increase in loans demand after a natural disaster; and the knowledge of borrowers and customers by local banks. The study by Schuwer et al. (2017) found that independent banks appear to react much better to natural disasters than the ones part of a bank holding group; they showed that this type of banks tend to strengthen their buffer against future income shocks and mitigate bankruptcy risks; this is especially true for highly capitalized independent banks. Local banks are

the focus of Kotter et al (2020) as well. Looking at floods in Germany, they showed that local banks are important to mitigate disaster risks and aid the recovery of disaster-struck small and medium enterprises. Duqi et al. (2021) reached a similar result; they showed that, in less competitive banking markets, following a natural disaster (tropical storm), *"banks increase the supply of real estate credit, especially refinancing of existing mortgages"*. Hursit et al. (2022) found an analogous outcome looking at Chinese regional state-owned City-Commercial Banks: they found that these banks tend to expand credit aggressively to respond to natural disasters in the affected cities; moreover, the post-disaster economic recovery is stronger in these cities.

Looking at the Italian case, Faiella and Natoli (2018) investigated the relationship between bank lending and catastrophe risk, focusing on floods. They found that lending to non-financial firms is negatively correlated with their flood risk exposure.

Our paper follows this stream of studies. Using the earthquake of 2012 that struck northern Italy as an exogenous shock, we look at the Italian local banks, represented by cooperative ones, comparing them with commercial banks. We are interested in understanding if local banks support the economic recovery in the aftermath of a natural disaster and whether there is a difference between local and commercial banks. Following the work of Nguyen et al. (2018) and Baltas, Fiordelisi and Mare (2022), we perform a Diff-in-Diff regression on both Cooperative and commercial banks, investigating whether local banks had a better reaction in terms of credit supply. Our findings are in line with the results listed above: local banks tend to increase the amount of loans disbursed in municipalities hit by the natural disaster.

To give support to these first results, we also performed a panel regression on bank lending, using control variables such as bank deposits, branches, and personal income. This further analysis led to similar results.

To our knowledge, this is the first study looking at the relation between natural disasters and the cooperative banking model at such a detailed level.

The rest of the paper is structured as follows: section 2 describes the dataset; section 3 has information about the econometric model used; section 4 illustrates results; finally, section 5, outlines the conclusions.

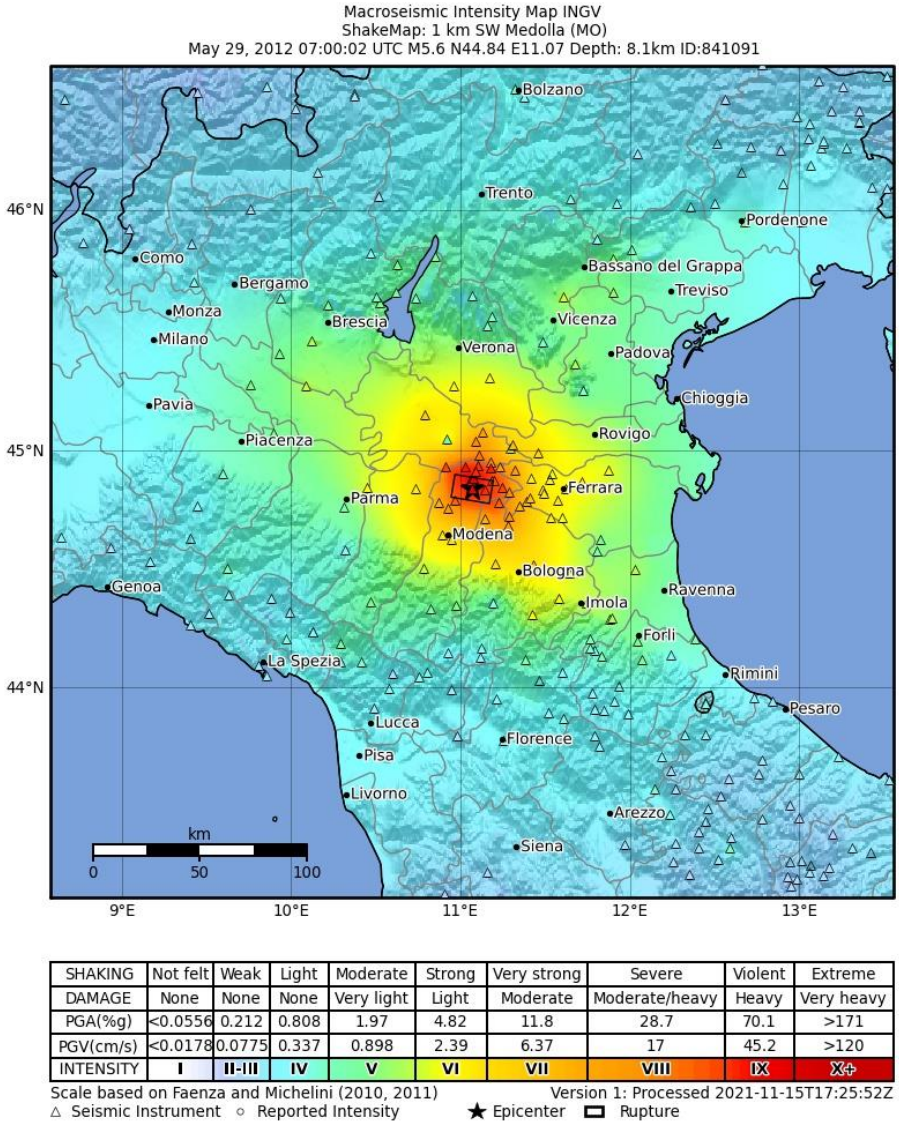
2. The dataset

The earthquake that hit Northern Italy in 2012 involved three regions: Lombardy, Veneto, and Emilia-Romagna. These regions represent the industrial core of the Italian economy: in 2012, the economic size of Lombardy accounted for more than 20% of the national GDP, whereas Veneto and Emilia-Romagna were close to 9%. The most catastrophic event took place in May 2012; however, aftershocks have been registered until July of the same year. Therefore, it is worth wondering whether the extreme event had consequences on these territories.

For the scope of the study, we collected annual data from 2010 to 2014, with a time interval of two years around the event; we gathered information about all the municipalities within the regions: 2,493 in total.
The banking data, for both Cooperative Banks (CCBs) and other banks (OBs), consist of loans and deposits to costumers, and bank branches at the municipal level; they come from the Bank of Italy's database. Other banks are simply defined as the difference between the whole industry and Cooperative Banks.
Moreover, to check the robustness of the estimation, we also made use of economic variables, such as personal income, which comes from the Ministry of Economic and Finance (MEF) database.
Out of the 2,493 municipalities involved, 44 of them were classified as hit by the earthquake. Data about the catastrophic event are publicly available on the website of the National Institute of Geophysics and Vulcanology (INGV). This is the public entity that monitors and analyzes earthquakes and volcanic activity across the country. Following INGV's data, cities hit were

ranked according to the Mercalli-Càncani-Sieberg (MCS) scale[2] (Sieberg, 1930). This scale measures the intensity of the earthquake according to the effects felt by the population and the visible damage taken by the buildings. Figure 1 depicts the ShakeMap developed by the INGV: it describes the microseismical intensity of the event that took place on May 29th. The dark-orange color is associated with a higher value of the earthquake's strength.

Table 1. ShakeMap of the earthquake.



SHAKING	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme
DAMAGE	None	None	None	Very light	Light	Moderate	Moderate/heavy	Heavy	Very heavy
PGA(%g)	<0.0556	0.212	0.808	1.97	4.82	11.8	28.7	70.1	>171
PGV(cm/s)	<0.0178	0.0775	0.337	0.898	2.39	6.37	17	45.2	>120
INTENSITY	I	II-III	IV	V	VI	VII	VIII	IX	X+

Scale based on Faenza and Michelini (2010, 2011) Version 1: Processed 2021-11-15T17:25:52Z
△ Seismic Instrument ○ Reported Intensity ★ Epicenter ▭ Rupture

Note: The ShakeMap depicts the epicenter and the larger area hit by the earthquake: the INTENSITY bar to the bottom has information about the intensity. The values are based on the work of Faenza and Michelini (Faenza & Michelini, 2010), who constructed a modified version of the usual MCS scale. The yellow, orange, and red areas are the most heavily hit.
Source: INGV https://shakemap.ingv.it/shake4/data/841091/current/products/intensity.jpg

[2] CFTI - MCS (ingv.it)

In total, 44 different municipalities reported an intensity on MCS scale higher than five, across six provinces. We take the value five as a threshold, since it is the value upon which damages are visible and the earthquake is felt by the population.

To account for stability, each time series has been transformed using the rate of change, and outliers have been filtered out. In addition, observations in which CCBs' loans and OBs loans are zero have been dropped off; this is the case where one municipality has no banks branch, or no Cooperative Bank branches. This step is to ensure comparability between municipality with at least one bank branch of both types (CCBs and OBs).

After data cleansing, we end up with 1,095 municipalities with at least one CCB bank branch, 16 of which have been hit by the earthquake in 2012.

Since the number of cities hit represents a small number of the whole sample (1.5%), robustness checks have been carried out looking at municipalities with at least one bank branch; this brings the size of the sample from 1,095 to 1,962 and the number of cities struck by the earthquake with at least one bank branch, from 16 to the original 44.
Table 1 lists all variables and their relative descriptive statistics.

Table 1. Descriptive statistics

Descriptive Statistics					
Variable	**Observations**	**Mean**	**St. Dev.**	**Min**	**Max**
$\Delta LoanCCB_{i,.t}$	3,801	-.0076	.1040	-.8889	.2895
$\Delta LoanOB_{i,.t}$	3,801	-.0265	.1362	-.9574	.2874
$\Delta INC_{i,t}$	3,791	-.0148	.0478	-.2337	.1298
$\Delta INC_2_{i,t}$	3,791	.0024	.0040	.0000	.0547
$\Delta DEP_CCB_{i,t}$	3,801	.0937	.1753	-.9341	.7096
$\Delta DEP_OB_{i,t}$	3,801	.0220	.1708	-1.7591	.4918
$\Delta BRN_CCB_{i,t}$	3,800	.0019	.0812	-1	2
$\Delta BRN_OB_{i,t}$	3,801	-.0161	.0829	-.5	1

Note. LOAN stands for bank loans; INC stands for income, whereas INC_2 represents income squared; DEP depicts bank deposits; finally, BRN stands for bank branch. Some variables, such as income, has 10 observations less than the others: this is due to missing data for some of the municipalities. The relatively small values for the minimum in some of the variables are due to the nature of the dataset: we are looking at banking data at the municipal level; the closing of one bank branch in one small municipality might lead to a substantial drop in the rate of change of either loans or deposits.
Note that each banking variable is computed for both Cooperative Credit Banks (CCBs) and Other Banks (OBs). Finally, the subscripts indicate municipality i at time t.

The picture that emerges from table 1 shows a reduction, on average, in the rate of change of loans for both CCBs and OBs, and in personal income within the regions under analysis under the analyzed time window. The period from 2010 to 2014 was, in fact, a difficult one for the Italian economy. The national GDP declined for two consequent years (-1.5% from 2011 to 2012 and -.7% from 2012 to 2013[3]), before recovering in 2014. It is important to keep this in mind during the rest of the analysis.

3. Regression model

Our dependent variable is always the rate of change of bank loans, computed for both CCBs and OBs. Hence, following the work by Nguyen and Wilson (2018), Koetter, Noth and Rehbein (2020), and Baltas, Fiordelisi and Mare (2022), we estimate the impact of the earthquake on bank lending using a plain Diff-in-Diff; three different dummies function as explanatory variables: $Time$, $Treatment$ and DiD, as shown in the equations below.

$$\Delta \boldsymbol{Loan_{i,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 Time} + \boldsymbol{\beta_2 Treatment} + \boldsymbol{\beta_3 DiD} + \boldsymbol{\varepsilon_{i,t}} \quad [\mathbf{1}]$$

Where: $\Delta Loan_{i,t}$ represents loans' rate of change and is computed for both CCBs and OBs; $Time$ equals 1 if $t \geq 2012$, 0 otherwise, independently of municipality i; $Treatment$ takes the value 1 if municipality i is hit by the earthquake, independently of time t; DiD is the interaction of the two; finally, α is the constant, and $\varepsilon_{i,t}$ are the errors.
Hence, β_3 is our variable of interest: the coefficient of DiD, in fact, catches the impact of the event on loans in each territory.

[3] Source: National Institute of Statistics (ISTAT).

To give support to the first estimation, we also performed a panel regression, including additional banking and economic variables. The equation below describes the second estimation.

$$\Delta \boldsymbol{Loan}_{i,t} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\Delta \boldsymbol{INC}_{i,t} + \boldsymbol{\beta_2}\Delta \boldsymbol{INC}_{2_{i,t}} + \boldsymbol{\beta_3}\Delta \boldsymbol{DEP}_{i,t} + \boldsymbol{\beta_4}\Delta \boldsymbol{BRN}_{i,t} + \quad [\mathbf{2}]$$
$$+ \boldsymbol{\beta_5}\boldsymbol{DiD} + \boldsymbol{\varepsilon}_{i,t}$$

Where: $\Delta Loan_{i,t}$ and DiD are defined as before; $\Delta INC_{i,t}$ is the rate of change of personal income per municipality i at time t, and $\Delta INC_2_{i,t}$ represents its square: this is to account for possible non-linear effects of personal income on loans; then, we have banking variables, once more computed for both CCBs and OBs: $\Delta DEP_{i,t}$ and $\Delta BRN_{i,t}$ (deposits and bank branches' rate of change, respectively); finally, α and $\varepsilon_{i,t}$ are once again the constant and the errors.

4. Results

4.1 Diff-in-Diff and panel regression

The following tables report the main results for the estimations.

Table 2 reports the results of the estimation of equation [1] for $\Delta Loan_{i,t}$: the coefficient of the dummy DiD is positive, and statistically significant for Cooperative Banks (CCBs); the same does not hold for other banks (OBs).
The result suggests that local banks kept supplying credit to costumers even in the aftermath of the disaster in the cities hit by the earthquake; this might have played an important role in the economic recovery of the territory.

Table 2. Diff-in-Diff results

	Diff-in-Diff Dependent variable: $\Delta Loan_{i,t}$	
Regressors	CCBs	OBs
$constant$	.0302*** (.0032)	-.0272*** (.0043)
$Time$	-.0514*** (.0036)	.0002 (.0051)
$Treatment$	-.0259 (.0258)	-.0095 (.0344)
DiD	.0644** (.0276)	.0410 (.0393)
Observations	3,801	3,801
Random effects	*Yes*	*Yes*
R^2	.0450	.0007
Chi-test (p-value)	.0000	.4621

*Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

It is worth noting the sign of the dummy *Time* for CCBs: from 2012 onwards, loan supply declined overall for CCBs; in the meantime, if we narrow down the analysis only to the municipalities struck by the natural disaster, we assist to an increase in loans' rate of change in the same time window. This testifies to the commitment of Cooperative Banks to keeping the credit channel open for firms and families in a difficult time during which there is a great need for resources.

However, it is necessary to deepen down the analysis: the R^2 is quite small, especially for OBs, and there might be other factors kicking-in that have been ignored in the first place. Therefore, we performed a panel regression as well, based on equation [2]. Table 3 collects the results.

Table 3. Panel regression results

Panel estimation Dependent variable: $\Delta Loan_{i,t}$		
Regressors	CCBs	OBs
$constant$	-.0316*** (.0027)	-.0296*** (.0025)
$\Delta INC_{i,t}$	.7660*** (.0512)	-.0779 (.0651)
$\Delta INC_2_{i,t}$	6.8400*** (.5857)	.8826 (.7511)
$\Delta DEP_{i,t}$	.1839*** (.0283)	.1608*** (.0127)
$\Delta BRN_{i,t}$	.0831*** (.0206)	.2395*** (.0259)
DiD	.0462*** (.0195)	.0179 (.0198)
Observations	3,790	3,791
Fixed effects	*Yes*	*No*
Random effects	*No*	*Yes*
R^2	.1706	.0723
F-test (p-value)	.0000	-
Chi-test (p-value)	-	.0000

*The decision to use fixed or random effects in the analysis is based on the results of the Hausman test. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

Panel estimation confirms our first findings. The R^2 has improved for both CCBs and OBs, whereas the dummy DiD, remains positive and statistically significant for cooperative banks. Adding control variables such as bank branches and deposits gives robustness to the estimation: following intuition, a higher number of branches and deposits leads to a higher disbursement of loans to customers, for both local and commercial banks. It remains true, however, that CCBs reacted better than OBs looking at the amount of loans disbursed in the cities struck by the natural disaster.

Finally, we conducted an additional robustness check. To ensure the soundness of the results, we enlarged the sample of municipalities. We performed another panel regression on a wider sample, which includes every city that has at least one bank branch.
Hence, the sample of municipalities under analysis increases from 1,095 to 1,962, the set of cities struck by the earthquake goes from 16 to the original 44, and the number of observations increases from 3,790 to 7,517.
Table 4 lists our findings for this last round of estimations.

Results are, once again, in line with the rest of the analysis. Widening our sample and looking at all municipalities, the R^2 increases and the estimation gains robustness; however, we do not find evidence of an increase in credit supply within those municipalities hit by the earthquake.
In other words, other banks did not increase the amount of loans disbursed to customers even when we look at the whole number of cities involved in the exogenous shock.
All the estimations we performed give support to our initial hypothesis: it is the presence of a Cooperative Banks that makes the difference; where there is a branch of CCBs, customers keep receiving loans to fulfill their needs, even in the aftermath of a natural disaster such as a devastating earthquake.

Table 4. Robustness check: panel regression results

Panel estimation: robustness check **Dependent variable: $\Delta Loan_OB_{i,t}$**	
Regressors	OBs
$constant$	-.0350*** (.0017)
$\Delta INC_{i,t}$	-.0330 (.0325)
$\Delta INC_2_{i,t}$	.1619 (.1656)
$\Delta DEP_{i,t}$	.3491*** (.0125)
$\Delta BRN_{i,t}$	.1949*** (.0196)
DiD	.0088 (.0117)
Observations	7,517
Random effects	*Yes*
R^2	.1158
Chi-test (p-value)	.0000

*The decision to run the regression with random effects is based on the results of the Hausman test. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

Once more, local knowledge and proximity to borrowers emerge as key factors. The development and organizational structure that differentiate the Cooperative banking model from the commercial one, enable local banks to support local economies even in the event of environmental shocks, "*limiting the exposure of areas to other risk*" (Blickle, Hamerling, & Morgan, 2021).

5. Conclusions

The aim of our paper was to investigate how different banking models react to an exogenous shock, such as a natural disaster. Using the earthquake that hit northern Italy in 2012 as a shock, we used a Diff-in-Diff and panel methodology to analyze the difference in credit supply between local and commercial banks.

The analysis is carried out to observe the effects of such a shock on credit supply for two different banking models, at the municipal level, over the period 2012-2014; the first estimation is carried out using Diff-in-Diff approach, comparing the municipalities in which there is CCBs and OBs that have been hit by the earthquake with those who were not.

This regression confirms our hypothesis that the presence of a Cooperative Bank branch results in an increase in credit supply to customers, even in the aftermath of a natural disaster.

To support this finding, we also performed a panel estimation including control variables, such as bank branches, deposits, and income.

The empirical results confirm the Diff-in-Diff. Municipalities in which there was a CCB, saw an increase in credit supply. An additional robustness check consists of performing panel regression on the whole sample of municipalities that include at least one banks branch, independently of its nature. Once more, the robustness check showed that when we look at all municipalities, there is no evidence of an increase in credit supply for OBs. This provides support for the idea that it is the presence of a Cooperative Bank that makes the difference, ensuring the expansion of the amount of loans provided to customers.

These findings suggest that their attention and connections to local and regional areas enable them to improve the economic response of businesses and families, strengthening the resilience of the territory. However, additional studies are needed to support this hypothesis.

Moreover, in the next future, it could be interesting investigating the behavior of the two banking models in the case of other types of disasters, such as floods and wildfires. Given the fragile nature of the Italian territory, it might be crucial posing these questions to avoid huge losses and backlash for the economy.

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