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Natural Disasters, Local banking, and Recovery lending: evidence from an Italian earthquake

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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 Italian earthquake of 2012 as exogenous shock, we investigate whether distinct banking models react differently. The baseline estimation is based on diff-in-diff approach. We show that Cooperative Banks, differently from commercial banks, do not interrupt the credit channel. To corroborate these findings, we also employ panel estimation, incorporating additional explanatory variables. The results are consistent with the baseline, indicating that local banks increased credit supply (recovery lending) in the territories affected by the earthquake, whereas there is no evidence for commercial banks. A series of robustness checks is carried out to bolster the results. Firstly, the sample size is enlarged by including a wider set of municipalities. Secondly, a placebo test is conducted by falsifying the date of the event and a propensity score matching analysis is performed on a control group. Finally, the same analysis is repeated on a random sample of municipalities. The robustness checks provide support to the baseline estimation. In municipalities affected by the earthquake, Cooperative Banks tend to increase loan supply, aiding the economic recovery. This does not emerge for other banks.

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1. Introduction

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 to address this question in recent 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 damage in recent years, leading to an increase in economic losses. They identify the direct and indirect economic impacts of such events: the former are identified by direct damage to assets and property, while the latter include the disruption of economic activities and short- and long-term economic losses. The authors conclude by suggesting how to mitigate the impact of disasters, as well as drawing lessons for policymakers and setting out 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. Indeed, in such environments, Berg and Schrader (2012) show that while credit demand increases due to volcanic activity, generally access to credit is restricted. Yet, they also found that bank-borrower relationships can lower these lending restrictions and that clients who are known to the institution are about equally likely to receive loans after volcanic eruptions occurred. Bos et al. (2022) identified that banks help clients smoothen consumption and support local recovery through their asset diversification strategy: their simulations showed that an increase in the (perceived) disaster probability due to climate change will be associated with decreased lending, a lower level of capital, less revenue, and higher holdings of government bonds in the pre-disaster steady state.

So, banks can play a vital role in helping affected communities to cope with natural disasters. Brei et al. (2024) suggested that the natural disaster shock is associated with persistent loan defaults and bank losses in the continental countries, whereas in the small island economies losses only start materializing after four years. In the two regions, the tropical storm recovery is thus credit-less. 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.

The study by Schuwer et al. (2019) found that independent banks appear to respond much better to natural disasters than those that are part of a bank holding group; they showed that this type of bank tends to strengthen its buffer against future income shocks and mitigate insolvency risks; this is especially true for highly capitalized independent banks. In addition, Cortés and Strahan (2017) provided evidence that a bank's physical presence in a market improves access to information about the quality of borrowers and the value of collateral. Above-average access to local information could allow banks to earn rents, but it also erected an obstacle to above-average access to local sales and/or securitization. These results suggest that banks protect rents particularly where they have a strong market presence, by sharply reducing lending in markets where they lend without a physical presence.
Local banks are also the focus of Koetter et al (2020). Using the example of floods in Germany, they show that local banks are important for mitigating disaster risks and supporting the recovery of small and medium-sized enterprises affected by disasters. Duqi et al. (2021) come to a similar conclusion, showing that in less competitive banking markets, after a natural disaster (tropical storm), *"banks increase the supply of real estate loans, especially the refinancing of existing mortgages"*. Hursit et al. (2022) found an analogous result when looking at China's regional state-owned City-Commercial Banks: they found that these banks tended to expand credit aggressively in response to natural disasters in the affected cities; moreover, the economic recovery was stronger in these cities after the disaster.
Chavaz (2016) compared local banks with diversified banks. They found that the former originated a higher share of new mortgages and small business loans in affected areas but sold a higher share of new mortgages to the secondary market. Thus, these results suggest a pattern of specialization, whereby loans in affected areas were increasingly originated by banks with special skills or incentives to seize opportunities in a distressed market but were increasingly transferred to intermediaries better able to support the associated risk. Indeed, local banks may find it more profitable to continue lending to affected areas than to lend elsewhere, due to their lending technology or ex-post incentives Indeed, local banks may find it more profitable to continue lending to affected areas than to lend elsewhere, due to their lending technology or ex-post incentives. Given their superior local knowledge, local banks may have an advantage in underwriting, monitoring and pricing new loans despite depressed or uncertain collateral values. They may also benefit more if originating and selling new loans generates immediate fee income, or if new loans have a positive impact on local house prices and activity. This relative profitability channel suggested that lending to affected areas should stem from local banks. Empirically, Cortés (2014), using detailed employment data on firm age and size, showed that an additional standard deviation of local finance could offset the negative effects of the disaster and lead to 1 to 2% higher employment growth in young or small firms. Thus, local lenders played an important and necessary role in the credit market, but also in creating jobs in the economy.

Our paper follows this line of research. Using the 2012 earthquake in northern Italy as an exogenous shock, we look at Italian local banks, represented by cooperative banks, and compare them with commercial banks. We are interested in understanding whether local banks support economic recovery after a natural disaster and whether there is a difference between local and commercial banks. Following the work of Nguyen and Wilson (2018) and Baltas, Fiordelisi and Mare (2022), we perform a diff-in-diff regression for both cooperative and commercial banks to investigate whether local banks have a better response in terms of credit supply. Our results are in line with the above: local banks tend to increase the amount of loans disbursed in municipalities affected by the natural disaster.

To support these initial findings, we also ran a panel regression on bank lending, using control variables such as bank deposits, branches and personal income. This further analysis produced similar results.

To the best of our knowledge, this is the first study to examine the relationship 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 provides information on the econometric model used; section 4 illustrates the results; finally, section 5 outlines the conclusions.

2. The Dataset

The earthquake that struck northern Italy in 2012 affected three regions: Lombardy, Veneto, and Emilia-Romagna. These regions represent the industrial core of the Italian economy: in 2012, Lombardy accounted for more than 20% of national GDP, while Veneto and Emilia-Romagna accounted for almost 9%. The most devastating event took place in May 2012, but aftershocks continued until July of that year. It is therefore worth asking whether the extreme event had an impact on these areas.

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 collected information on all municipalities within the regions: 2,493 in total.

Banking data, both for cooperative banks (CCBs) and other banks (OBs), consist of loans and deposits to customers and bank branches at municipal level; they are taken from the Bank of Italy's database. Other banks are simply defined as the difference between the whole sector and the cooperative banks.

In order to check the robustness of the estimation, we also used economic variables such as personal income from the Ministry of Economy and Finance (MEF) database.

Of the 2,493 municipalities affected, 44 were classified as affected by the earthquake. Data on the disaster is publicly available on the website of the National Institute of Geophysics and Vulcanology (INGV). This is the public institution that monitors and analyses earthquakes and volcanic activity throughout the country. Based on the INGV data, the affected cities were ranked according to the Mercalli-Càncani-Sieberg (MCS) scale (Sieberg, 1930). This scale measures the intensity of the earthquake according to the effects felt by the population and the visible damage to buildings.

Figure 1 shows the ShakeMap developed by the INGV: it describes the microseismical intensity of the 29 May event. The dark orange color is associated with a higher value of the earthquake's magnitude.

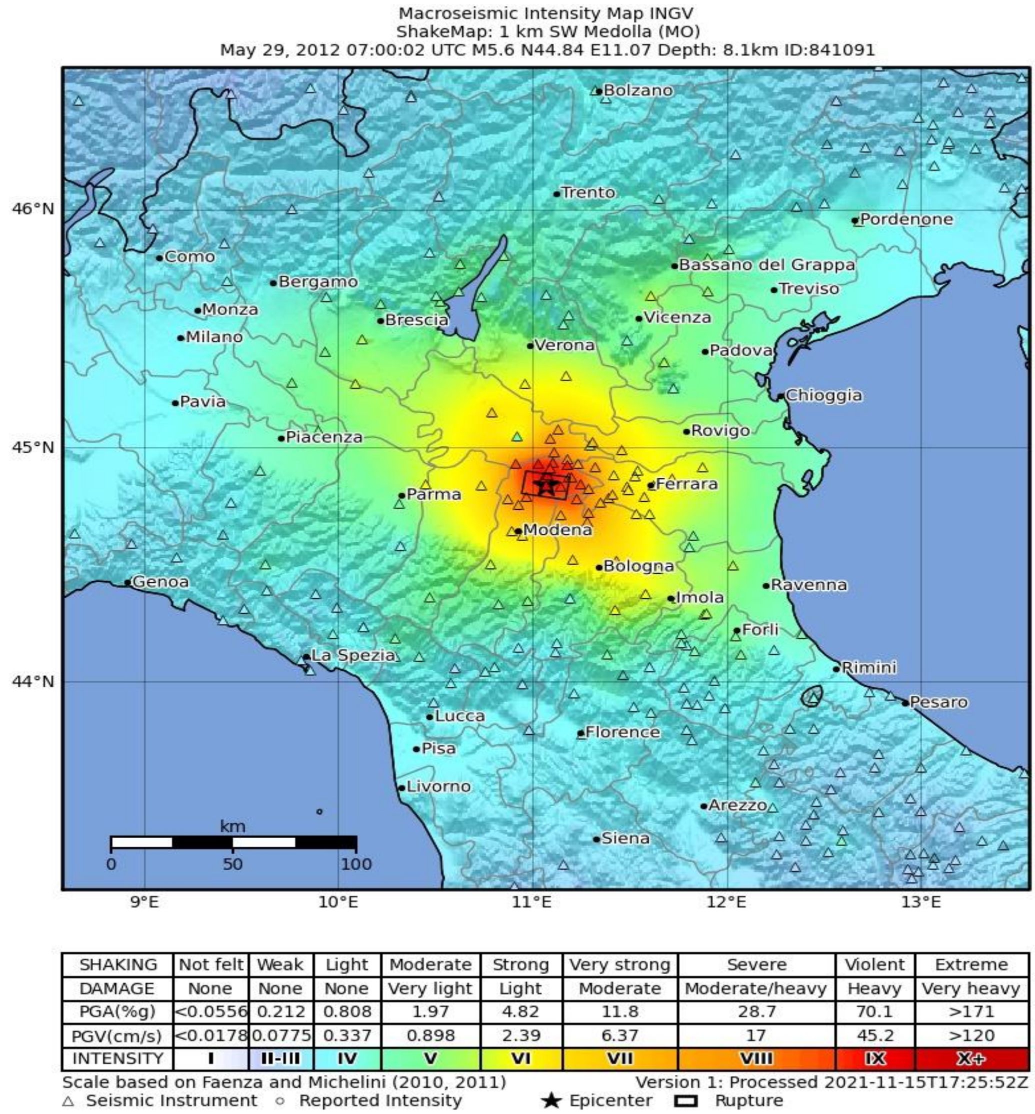

Figure 1: ShakeMap of the earthquake

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 (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

In total, 44 different municipalities in six provinces reported an intensity higher than five on the MCS scale. We use five as a threshold because this is the level at which damage is 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, in order to carry out the baseline estimation, observations where the loans of CCBs and OBs are zero have been dropped; this is the case when a municipality has no bank branch or no cooperative bank branches. This step ensures comparability between municipalities 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 were affected by the 2012 earthquake.
As the number of cities affected represents a small proportion of the total sample (1.5%), various robustness checks were carried out by looking at municipalities with at least one bank branch; this increases the sample size from 1,095 to 1,962 and the number of cities affected by the earthquake with at least one bank branch from 16 to the original 44.
Table 1 lists all the variables and their corresponding descriptive statistics.

Table 1: Descriptive statistics

Variable	Observations	Mean	St. Dev.	Min	Max
$\Delta LoanCCB_{i,.t}$	3,801	-0.0076	0.1040	-0.8889	0.2895
$\Delta LoanOB_{i,.t}$	3,801	-0.0265	0.1362	-0.9574	0.2874
$\Delta INC_{i,t}$	3,791	-0.0148	0.0478	-0.2337	0.1298
$\Delta INC\_2_{i,t}$	3,791	0.0024	0.0040	0.0000	0.0547
$\Delta DEP\_CCB_{i,t}$	3,801	0.0937	0.1753	-0.9341	0.7096
$\Delta DEP\_OB_{i,t}$	3,801	0.0220	0.1708	-1.7591	0.4918
$\Delta BRN\_CCB_{i,t}$	3,800	0.0019	0.0812	-1	2
$\Delta BRN\_OB_{i,t}$	3,801	-0.0161	0.0829	-0.5	1

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 that, on average, the rate of change of loans, both for CCBs and for OBs, and of personal income within the regions under analysis decreased over the period analyzed. The period from 2010 to 2014 was indeed a difficult one for the Italian economy. National GDP fell for two consecutive years (-1.5% from 2011 to 2012 and -.7% from 2012 to 2013), before recovering in 2014.

3. Regression model

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

$$\Delta Loan_{i,t} = \alpha + \beta_1 Time + \beta_2 Treatment + \beta_3 DiD + \varepsilon_{i,t} \tag{1}$$

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.

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

$$\Delta Loan_{i,t} = \alpha + \beta_1 \Delta INC_{i,t} + \beta_2 \Delta INC_{2_{i,t}} + \beta_3 \Delta DEP_{i,t} + \beta_4 \Delta BRN_{i,t} + \beta_5 DiD + \varepsilon_{i,t} \tag{2}$$

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 Baseline estimation

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).

Table 2: Diff-in-Diff estimation. Dependent variable: $\Delta Loan_{i,t}$

Regressors	**CCBs**	**OBs**
$constant$	0.0302*** (0.0032)	-0.0272*** (0.0043)
$Time$	-0.0514*** (0.0036)	0.0002 (0.0051)
$Treatment$	-0.0259 (0.0258)	-0.0095 (0.0344)
DiD	0.0644** (0.0276)	0.0410 (0.0393)
Observations	3,801	3,801
Random effects	*Yes*	*Yes*
R^2	0.0450	0.0007
Chi-test (p-value)	0.0000	0.4621

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

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.

It is worth noting the sign of the dummy Time for CCBs: from 2012 onwards, the supply of credit for CCBs as a whole decreased; in the meantime, if we restrict the analysis to municipalities affected by the natural disaster, we contribute to an increase in the rate of change of credit over the same period. This demonstrates the commitment of the cooperative banks to keep the credit channel open to businesses and families at a difficult time when there is a great need for resources.

However, the R^2 is quite small, especially for OBs, and there may be other factors at play that have not been considered. Therefore, we also ran a panel regression based on equation (2). Table 3 summarizes the results.

Table 3: Panel regression. Dependent variable: $\Delta Loan_{i,t}$

Regressors	CCBs	OBs
$constant$	-0.0316*** (0.0027)	-0.0296*** (0.0025)
$\Delta INC_{i,t}$	0.7660*** (0.0512)	-0.0779 (0.0651)
$\Delta INC\_2_{i,t}$	6.8400*** (0.5857)	0.8826 (0.7511)
$\Delta DEP_{i,t}$	0.1839*** (0.0283)	0.1608*** (0.0127)
$\Delta BRN_{i,t}$	0.0831*** (0.0206)	0.2395*** (0.0259)
DiD	0.0462*** (0.0195)	0.0179 (0.0198)
Observations	3,790	3,791
Fixed effects	*Yes*	*No*
Random effects	*No*	*Yes*
R^2	0.1706	0.0723
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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The panel estimation confirms our initial findings. The R^2 has improved for both CCBs and OBs, while the dummy DiD remains positive and statistically significant for cooperative banks. The addition of control variables such as bank branches and deposits adds robustness to the estimation: intuitively, a higher number of branches and deposits leads to higher loan disbursement to customers, for both local and commercial banks. The signs and significance levels of the control variables are consistent with the results obtained by Nguyen and Wilson (2018). However, it remains true that CCBs responded better than OBs in terms of the amount of loans disbursed in the cities affected by the natural disaster.

4.2 Robustness checks

We conducted several robustness checks to ensure the soundness of the results. First, we expanded the sample of municipalities by running a panel regression on a larger sample that includes each city that has at least one bank branch.

This increases the sample of municipalities analyzed from 1,095 to 1,962, the number of cities affected by the earthquake from 16 to the original 44, and the number of observations from 3,790 to 7,517. We then repeat our estimation for OBs only. Table 4 shows our results for this last round of estimation.

Table 4: Robustness check: panel regression on a wider sample. Dependent variable: $\Delta Loan_{i,t}$

Regressors	**OBs**
$constant$	-0.0350*** (0.0017)
$\Delta INC_{i,t}$	-0.0330 (0.0325)
$\Delta INC\_2_{i,t}$	0.1619 (0.1656)
$\Delta DEP_{i,t}$	0.3491*** (0.0125)
$\Delta BRN_{i,t}$	0.1949*** (0.0196)
DiD	0.0088 (0.0117)
Observations	7,517
Random effects	*Yes*
R^2	0.1158
Chi-test (p-value)	0.0000

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

The results are consistent with the rest of the analysis. Extending the sample to include all municipalities increases the R^2 and makes the estimation more robust, but we find no evidence of an increase in the supply of credit by OBs in the municipalities affected by the earthquake.

In other words, other banks did not increase the amount of loans disbursed to customers, even when we look at the total number of cities affected by the exogenous shock.

The second check is a placebo test: we artificially impose the date of the exogenous shock one year earlier, in 2011, and run the same estimation described in equation (2). Since we are mainly interested in the effect of the earthquake on CCBs, this check is performed only on this type of banks. The results are presented in Table 5 Contrary to the baseline estimation (Table 2), the DiD dummy loses its significance in this case: shifting the date of the shock does not lead to an increase in credit supply to the earthquake-affected municipalities, at least for CCBs. The placebo test confirms our hypothesis: Cooperative banks tend to increase the supply of credit, especially where the natural disaster had its more serious consequences.

Table 5: Robustness check: Placebo test (falsify date). Dependent variable: $\Delta Loan_{i,t}$

Regressors	**CCBs**
$constant$	-0.0726*** (.0026)
$\Delta INC_{i,t}$	0.9263*** (0.0574)
$\Delta INC\_2_{i,t}$	7.8636*** (0.6824)
$\Delta DEP_{i,t}$	0.5084*** (0.0085)
$\Delta BRN_{i,t}$	0.1373*** (0.0217)
DiD	0.0138 (0.0195)
Observations	3,878
Random effects	*Yes*
R^2	0.5352
Chi-test (p-value)	0.0000

The date of the event has been artificially imposed to 2011 in this case.
The decision to run the regression with random effects is based on the results of the Hausman test.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In addition to these initial checks, we also carried out the panel estimation on a control group established by Propensity Score Matching (PSM), which identifies a group of cities with the same characteristics. The results are presented in Table 6. The result is consistent with the other estimations: once again, the coefficient of the DiD dummy is positive and statistically significant for CCBs, but not for other banks. Therefore, choosing a control group with the same characteristics as the original group, the positive effect on credit supply remains for Cooperative Banks.

Table 6: Robustness check: Propensity Score Matching (PSM). Dependent variable: $\Delta Loan_{i,t}$

Regressors	**CCBs**	**OBs**
$constant$	-0.0194 (0.0127)	-0.0321*** (0.0076)
$\Delta INC_{i,t}$	0.4556* (0.2522)	0.0932 (0.1753)
$\Delta INC\_2_{i,t}$	0.4573 (3.0074)	0.9774 (2.0567)
$\Delta DEP_{i,t}$	0.1251*** (0.0440)	0.2902*** (.0444)
$\Delta BRN_{i,t}$	0.1171 (0.4170)	0.2069** (0.0831)
DiD	0.0327* (0.0172)	0.0115 (0.0110)
Observations	121	346
Fixed effects	*No*	*No*
Random effects	*Yes*	*Yes*
R^2	0.1275	0.1399
F-test (p-value)	-	-
Chi-test (p-value)	.0049	.0000

PSM has been estimated using one-to-one matching to define the control group.
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

Finally, Table 7 collects the results of the last robustness check: we ran the panel regression in equation [2] on a random sample of municipalities. In order to have a result comparable to the baseline estimate, we randomly selected 44 municipalities and considered them as having been affected by the earthquake. The result is consistent with the placebo test: when we switch to random municipalities, the dummy DiD is insignificant. There is no evidence of a general increase in the supply of credit by CCBs: the effect appears only when we focus on the cities affected by the exogenous shock.

Table 7: Robustness check: random sampling. Dependent variable: $\Delta Loan_{i,t}$

Regressors	**CCBs**	**OBs**
$constant$	-0.0631*** (0.0023)	-0.0358*** (0.0018)
$\Delta INC_{i,t}$	0.9447*** (0.0569)	0.0441 (0.0352)
$\Delta INC\_2_{i,t}$	8.9409*** (0.6958)	0.3090 (0.2169)
$\Delta DEP_{i,t}$	0.3630*** (0.0101)	0.3803*** (0.0148)
$\Delta BRN_{i,t}$	0.1423*** (0.0233)	0.1943*** (0.0228)
DiD	-0.0078 (0.0244)	-0.0041 (0.0239)
Observations	3,878	7,517
Fixed effects	*Yes*	*Yes*
Random effects	*No*	*No*
R^2	0.5255	0.1156
F-test (p-value)	0.0000	0.0000
Chi-test (p-value)	-	-

We randomly selected 44 municipalities and considered them as hit by the earthquake.
The decision to run the regression with random effects is based on the results of the Hausman test.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All the estimates we have made support our initial hypothesis: it is the presence of a Cooperative Bank that makes the difference; where there is a CCB branch, customers continue to receive credit to meet their needs, even after a natural disaster such as an earthquake.

Local knowledge and proximity to borrowers emerge as key factors. The development and organizational structure that distinguishes the Cooperative Banking model from the commercial model enables local banks to support local economies even in the event of environmental shocks, "limiting the exposure of areas to other risks" (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 Cooperative Bank increase 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. A series of robustness checks have been performed to confirm the results: a second panel regression on a wider sample, placebo test, propensity score matching, and a random sampling of municipalities. All of these checks showed that the presence of CCBs is fundamental to the credit supply in a municipality hit by the earthquake, while no evidence emerges 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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References

[1] Baltas, K., Fiordelisi, F., & Mare, D. S. (2022). "Alternative Finance after Natural Disasters". British Journal of Management, 117-137.
[2] Berg, G., & Schrader, J. (2012). "Access to credit, natural disasters, and relationship lending". Journal of Financial Intermediation, Vol. 21, Issue 4, 549-568.
[3] Blickle, K. S., Hamerling, S. N., & Morgan, D. P. (2021). "How bad are weather disasters for banks?". FRB of New York Staff Report N. 990.
[4] Bos, J. W., Li, R., & Sanders, M. W. (2022). "Hazardous lending: The impact of natural disasters on bank asset portfolio". Economic Modelling, Vol. 108.
[5] Botzen, W. W., Deschenes, O., & Sanders, M. (2019). "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies". Review of Environmental Economics and Policy.
[6] Brei, M., Mohan, P., Barahona, A. P., & Strobl, E. (2024). "Transmission of natural disasters to the banking sector: Evidence from thirty years of tropical storms in the Caribbean". Journal of International Money and Finance, Vol. 141.
[7] Chavaz, M. (2016). Dis-Integrating Credit Markets: Diversification, Securitization, and Lending in a Recovery. Bank of England Working Paper No. 617.
[8] Cortés, K. R. (2014). "Rebuilding after Disaster Strikes: How Local Lenders Aid in the Recovery". FRB of Cleveland Working Paper No. 14-28.
[9] Cortés, R. K., & Strahan, E. P. (2017). "Tracing out capital flows: How financially integrated banks respond to natural disasters". Journal of Financial Economics Vol. 125, Issue 1, 182-199.
[10] Duqi, A., McGowan, D., Onali, E., & Torluccio, G. (2021). "Natural disasters and economic growth: the role of banking market structure". Journal of Corporate Finance, Forthcoming.
[11] European Central Bank. (2021). Climate change and monetary policy in the euro area. Occasional Paper Series, No. 271.
[12] Faenza, L., & Michelini, A. (2010). "Regression analysis of MCS intensity and ground motion parameters in Italy and its application in ShakeMap". Geophysical Journal International, 1138-1152.
[13] Faiella, I., & Natoli, F. (2018). "Natural catastrophes and bank lending: the case of flood risk in Italy". Banca d'Italia, Questioni di Economia e Finanza (Occasional Paper), 457.
[14] Hursit, S. C., Seungjoon, O., & Srinivasan, S. (2022). "Natural disasters and the role of regional lenders in economic recovery". Journal of Empirical Finance, 116-132.
[15] Koetter, M., Noth, F., & Rehbein, O. (2020). "Borrowers under water! Rare disasters, regional banks, and recovery lending". Journal of Financial Intermediation, Volume 43.

[16] Nguyen, L., & Wilson, J. O. (2018). "How Does Credit Supply React to a Natural Disaster? Evidence from the Indian Ocean Tsunami". European Journal of Finance, Forthcoming.
[17] Schuwer, U., Lambert, C., & Noth, F. (2019). "How Do Banks React to Catastrophic Events? Evidence from Hurricane Katrina". European Finance Review 23(1), 75-116.
[18] Sieberg, A. (1930). "Geologie der Erdbeben". Handbuck der Geophysik, 2, 4, 552-555.