Flood risk and credit market conditions for Italian SMEs*

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Abstract

We study the impact of flood risk on the credit supply to Italian small and medium-sized enterprises (SMEs) over the period 2008−2019, with the aim of detecting which geographical areas should be targeted (through local government interventions, such as loan guarantees) to mitigate its negative effects on credit market conditions. We contribute to the existing literature in two ways. First, using sign restrictions to identify a structural-form model estimated on a granular dataset of new loan volumes and interest rates, we construct a province-level (NUTS-3) indicator of credit supply for Italian SMEs. Second, our empirical approach, based on rolling-window estimation, allows us to assess the time-varying effect of greater exposure to flood risk on credit tightening across Italian provinces. The empirical findings reveal that southern provinces exhibit tighter credit market conditions than those in the Centre-North. The full-sample analysis provides only limited evidence that flood risk contributes to tighter provincial credit conditions. However, the time-varying analysis reveals that this relationship is considerably stronger from 2016 onward, corresponding to a period of increased concern about climate change.

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1 Introduction

Over the past few decades, natural disasters have become increasingly frequent and severe, generating substantial economic losses and financial disruptions. Among these climate-related events, river and coastal floods represent some of the most damaging hazards. This paper assesses the role of ex-ante flood risk in shaping credit supply to small and medium-sized enterprises (SMEs) in Italian provinces over the period $2008Q1 - 2019Q4$. More specifically, we investigate whether provinces that are more exposed to flood risk face tighter credit market conditions, reflected in lower lending volumes and higher borrowing costs.

The existing literature has mostly examined the impact of physical climate risk on credit markets by analyzing interest rates and loan volumes separately. One strand of the literature focuses on the effects of climate risk on lending rates. For the United States, a few studies explore the role played by long-term physical risks, such as sea level rise, in shaping mortgage interest rates (see Baldauf et al., 2020, Bernstein et al., 2019, and Nguyen et al., 2022). Correa et al. (2022) study the interaction between physical risk (i.e., hurricanes) and realized losses due to the occurrence of a natural disaster, and find that syndicated loans bear a risk premium for at-risk but unaffected borrowers. Acharya et al. (2022) explore the pricing of observed heat stress in U.S. municipal and corporate bond markets. For Europe, Altavilla et al. (2024) control for firm-specific default rates and focus on transition risk (proxied by firms' carbon emissions) to assess its impact on bank loan interest rates. As for physical risk, Garbarino and Guin (2021) provide evidence for the United Kingdom, showing that lenders substantially adjust mortgage contract terms (both interest rates and loan amounts) in response to flood risk.

Another strand of the literature investigates the impact of natural disasters on loan volumes. A number of studies focus on the demand for credit in affected areas arising from the need to rebuild destroyed or damaged physical capital (see Berg and Schrader, 2012, Cortés and Strahan, 2017, Koetter et al., 2020, Chavaz, 2016, and Celil et al., 2022). Noth and Schüwer (2023) examine the effect of the occurrence of weather-related natural disasters on borrower default risk in the United States. More recently, there have been a few contributions providing evidence on the effects of flood risk on lending volumes in Europe. Barbaglia, Fatica, and Rho (2023) focus on the impact of province-specific flood risk and the occurrence of flooding on credit market conditions for new loans to SMEs in Europe, by disentangling the effect on interest rates, default rates, and loan volumes. Clò et al. (2024), using a dataset on landslides and floods affecting Italian municipalities from 2010 to 2018, investigate the impact of such natural disasters on firms' survival and performance.

We contribute to the academic literature in two ways. First, we examine the effect of ex-ante flood risk on province-level credit supply to SMEs in Italy by constructing a novel province-level credit supply indicator (CSI), which combines information from new loan volumes and lending rates. Our approach differs from existing measures of credit supply in Italy. While the Bank of Italy constructs credit supply indicators at the macro-regional level using information from the Regional Bank Lending Survey (RBLS), and Barone et al. (2018), following Greenstone et al. (2020), identify provincial credit supply through interactive fixed effects in a panel regression estimated only on outstanding loans, we identify credit supply using sign restrictions imposed on new loan volumes and lending interest rates.[1] We use new loans in the construction of the credit supply indicator since they capture the bank's active credit decisions at the margin, reflecting current risk appetite and lending conditions. In contrast, loan stocks are persistent state variables contaminated by past contracts, borrower repayments, and non-performing loans write-offs making stock-based indicators reflect historical debt dynamics rather than true contemporaneous supply shifts.

Second, whereas the existing literature has largely focused on average effects of flood risk exposure on credit market conditions, our empirical framework allows us to investigate the time-varying contribution of flood risk exposure to provincial credit supply in Italy.

Our empirical findings document a pronounced North-South divide in credit conditions, with Southern Italian provinces experiencing greater credit constraints. After controlling for differences in local economic development, we find limited evidence that exposure to flood risk contributes to tighter credit conditions at the provincial level, with stronger effects in less economically developed provinces. However, statistical significance is confined to the high-probability flood risk scenario. The time-varying analysis suggests that exposure to high flood risk is associated with a positive and statistically significant effect on credit conditions tightening from 2016 onward.

Our findings provide useful insights for businesses and policymakers in identifying which

[1] The Regional Bank Lending Survey conducted by the Bank of Italy extends the Eurosystem Bank Lending Survey (BLS) published by the European Central Bank (ECB) at a more geographically and sectorally disaggregated level (see e.g., Bank of Italy, 2025 for further details on the RBLS). See also Del Giovane et al. (2011) for an empirical analysis based on BLS data for Italy.

geographical areas may require targeted local government support, for instance, through loan guarantees granted to companies operating in areas with high flood risk.

The paper is organized as follows. Section 2 describes the empirical methodology. Section 3 presents the data and empirical results. Section 4 extends the analysis to also include the COVID-19 period. Finally, Section 5 concludes.

2 Empirical methodology

In our empirical analysis, we investigate the effects of exposure to coastal and river flood risk on the supply of credit to SMEs in Italian provinces using a two-stage approach. In the first stage, we construct a credit supply indicator (CSI) at the NUTS-3 level (corresponding to Italian provinces) using theory-driven sign restrictions. Higher values of the CSI indicate tighter credit supply conditions. More specifically, we first estimate the following multivariate static equation model:

$$y_{i,b,k,t} = \beta X_{i,b,k,t} + \gamma z_{k,t} + \delta W_b + \mu_k + \mu_t + u_{i,b,k,t} \tag{1}$$

where $y_{i,b,k,t}$ is a 2×1 vector that contains the logarithm of new loan volumes and the interest rate on loan i, granted to firm b, located in province k, during quarter t. Moreover, $X_{i,b,k,t}$ includes the logarithm of the loan term (measured in quarters) and the collateral ratio, while $z_{k,t}$ is the annual real GDP per capita of province k in quarter t.[2] We also include a dummy variable (W_b) that takes the value one for firms receiving more than one loan and zero otherwise. Furthermore, μ_k and μ_t are, respectively, province- and time-fixed effects. Finally, $u_{i,b,k,t} \sim \mathcal{N}(0, \Sigma)$ is a 2×1 vector of zero-mean error terms, with covariance matrix (Σ), which is not assumed to be diagonal. The model in equation (1) is estimated equation-by-equation, separately for each dependent variable, using ordinary least squares (OLS).

Then, for each province k, we assume the following relationship between the reduced-form innovations $u^{(k)}_{i,b,t}$, estimated from equation (1), and the structural shocks:

$$u^{(k)}_{i,b,t} = B^{(k)}_0 \; \varepsilon^{(k)}_{i,b,t} \tag{2}$$

where $B^{(k)}_0$ is the province-specific impact multiplier matrix, which captures the contem-

[2] Since real GDP per capita at the NUTS3 level is available only at an annual frequency, we repeat the annual observation for each quarter of the corresponding year.

poraneous effects of the structural shocks on new loan volumes and interest rates, and $\varepsilon_{i,b,t}^{(k)} \sim \mathcal{N}(0, I_2)$ are the structural shocks, whose variances are normalized to one such that $E(u_{i,b,t}^{(k)} u_{i,b,t}^{(k)\prime}) = \Sigma^{(k)} = B_0^{(k)} B_0^{(k)\prime}$.

For each province, the indicator of credit tightening conditions is constructed as a weighted average of new lending and interest rate on loans, where the weights correspond to the impact responses of the two variables to credit supply shocks. These shocks are identified at the provincial level by imposing theory-driven sign restrictions on the impact multiplier matrix defined in equation (2). This identification strategy consists of searching for admissible realizations of the structural shocks ($\tilde{\varepsilon}_{i,b,t}^{(k)}$) that satisfy the imposed sign restrictions on the impact response of the variables of interest (in our case, new lending and interest rate). To generate a set of candidate solutions of the impact impulse response (and hence of the structural shocks), we use the algorithm proposed by Rubio-Ramírez et al. (2010) (also known as the Householder transformation approach). More specifically, we randomly draw 2×2 matrices $\tilde{H} \sim \mathcal{N}(0, I_2)$, with independent standard Gaussian entries, and compute their QR decomposition, $\tilde{H} = QR$, where Q is a 2×2 orthogonal matrix and R is a 2×2 upper triangular matrix.[3] For each draw, the candidate impact multiplier matrix is computed as $B_0^{(k)} = \tilde{B}_0^{(k)} Q$, where $\tilde{B}_0^{(k)}$ denotes the Cholesky decomposition of the province-specific reduced-form covariance matrix $\Sigma^{(k)}$.[4] We discard the impact response matrices that do not satisfy the sign restrictions. We repeat the algorithm until we save 10 000 impulse responses for each of the 103 NUTS3 provinces.

The analysis focuses on the identification of negative credit supply shocks, which allows us to construct a measure of credit supply contraction. Specifically, we impose that such shocks lead to opposite movements in new lending and interest rates: a contraction in loan volumes and an increase in interest rates. This identification strategy follows a well-established empirical literature that employs sign restrictions in Vector Autoregressions (VAR) to investigate the macroeconomic effects of credit supply shocks (see, e.g., Gambetti and Musso, 2017; Mumtaz et al., 2018, among others).[5]

Based on the identification of negative credit supply shocks at the provincial level, we construct a credit supply indicator that captures the degree of tightening in credit condi-

[3]To ensure uniqueness of the QR decomposition of the independent standard Gaussian matrix, the diagonal elements of the upper triangular matrix R are constrained to be positive.

[4]The covariance matrix $\Sigma^{(k)}$ is computed from the subset of residuals from equation (1) that corresponds to province k.

[5]Unlike the aggregate time-series setting considered in the VAR literature, our analysis relies on loan-level observations of newly originated loans. Individual loan contracts are observed only at the time of origination and are not followed over time, preventing the estimation of a VAR model. Consequently, we identify credit supply shocks within a static simultaneous equation framework using contemporaneous sign restrictions.

tions across Italian provinces. The rationale behind the indicator is that credit conditions become tighter when banks simultaneously reduce the amount of new lending and increase lending rates on new loans. More specifically, for each province k, we compute the credit supply indicator (CSI) as follows:

$$CSI_{i,b,t}^{(k)} = \log(Loans^{(k)})_{i,b,t}^{-1} \times |\omega_k^{loans}| + int.rate_{i,b,t}^{(k)} \times \omega_k^{int.rate} \tag{3}$$

where $Loans_{i,b,t}^{(k)}$ is the logarithm of the new loan amounts issued for loan i, granted to firm b, in province k, during quarter t, while $int.rate_{i,b,t}^{(k)}$ is the interest rate charged on that specific loan. Furthermore, ω_k^{loans} and $\omega_k^{int.rate}$ are the estimated median responses (from the set of identified impact multiplier matrices) of, respectively, new loans and interest rates to negative credit supply shocks for each province k. In equation (3), computing the inverse of new loan volumes ensures that decreases in lending correspond to higher values of the credit supply indicator. Moreover, because new lending decreases following a negative credit supply shock, the corresponding weight is taken in absolute value. The weights are normalized to sum to one, allowing the CSI to be interpreted as a weighted average of its two components. This indicator is computed for each of the 10 000 retained impact multiplier matrices. Therefore, the province-level CSI is obtained by taking the median of its empirical distribution. Finally, we normalize the province-level indicators of credit supply contraction to take values between zero and one by subtracting the minimum value across the 103 provinces and dividing by the corresponding range (i.e., the difference between the maximum and minimum values).

In the second stage of the analysis, we investigate the role of ex-ante flood risk in shaping provincial credit market conditions by estimating: (a) the average effect over the $2008-2019$ period; (b) the time-varying contribution (e.g., at the yearly level). In particular, we estimate the following cross-sectional regression:

$$CSI_k = \tau + \phi Risk_k + \theta z_{k,2008} + \psi(Risk_k \times z_{k,2008}) + \eta_k \tag{4}$$

As for case (a), CSI_k denotes the median credit supply indicator for province k, constructed using information on new loan volumes and lending rates over the full sample period. The variable $Risk_k$ captures ex-ante flood risk exposure and is measured as the share of provincial surface area exposed to flood risk, expressed as a percentage of the total area of the province. We consider three alternative flood hazard scenarios (high-, medium-, and low-probability hazards) and estimate the regression separately for each scenario. Moreover, $z_{k,2008}$ denotes provincial GDP per capita in 2008, which controls for differences in the initial level of local economic development across provinces. Using the initial level of GDP per capita helps alleviate concerns that contemporaneous economic conditions may be jointly determined with credit market outcomes. Finally, we include an interaction term between flood risk exposure and GDP per capita allowing the effect of flood risk exposure on credit supply conditions to vary with the level of provincial economic development.

As for case (b), equation (4) is estimated using, as the dependent variable, the median credit supply indicator for each province constructed from new lending volumes and interest rates observed in year t. Specifically, we estimate a sequence of annual cross-sectional regressions, one for each year in the sample, in which the 103 province-level credit supply indicators are regressed on the time-invariant measure of ex-ante flood risk.

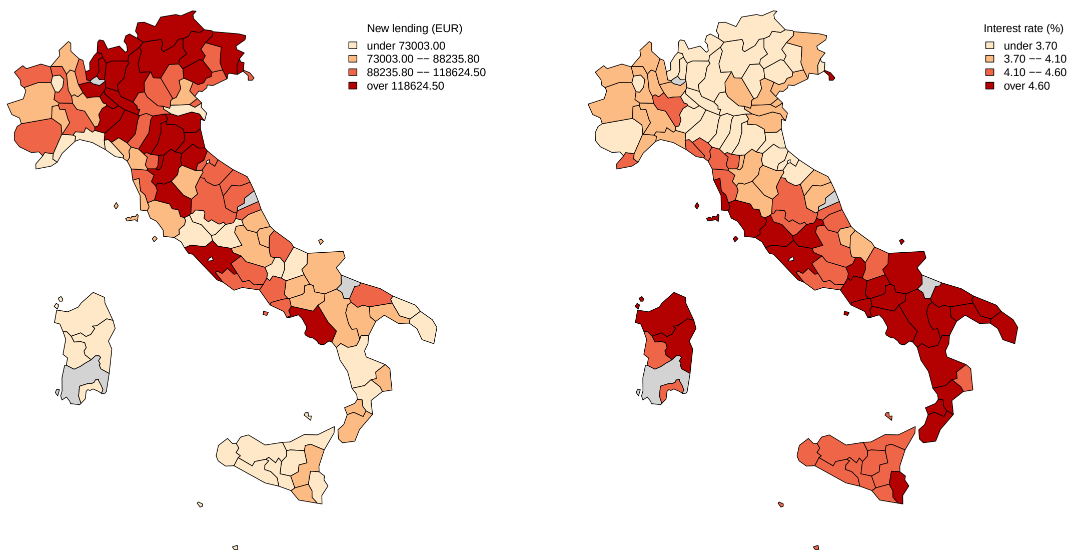
3 Empirical analysis

3.1 Data

The multivariate static equation model described in equation (1) is estimated using quarterly loan-level information on credit market conditions for small and medium-sized enterprises (SMEs), together with annual data on economic activity, across the 103 Italian NUTS-3 provinces over the period $2008Q1 - 2019Q4$. Credit market variables are constructed from loan-level data (LLD) obtained from the European Datawarehouse (EDW), a centralized platform that collects, validates, and disseminates detailed loan-level information for European asset-backed securities (ABS) since 2012.[6] Although EDW provides credit market data beyond $2019Q4$, we exclude observations related to the COVID-19 period in our baseline analysis. In addition, from $2021Q3$ onward, ABS issuers are required to report loan-level information using both the ECB and ESMA templates. Therefore, restricting the sample to $2019Q4$ ensures that all observations are collected under the same reporting template (i.e., the ECB template), thereby preserving consistency in reporting standards and asset definitions. As a robustness check, we extend the sample to include the COVID-19 period and re-estimate the empirical model using data up to $2021Q2$ (see Section 4). Under the ECB template, EDW reports loan-level data for several asset classes, including auto loans, SME loans, commercial real estate, residential

[6]ABS issuers are required to submit loan-level data using two reporting templates: the ECB and ESMA templates. The ECB template has been mandatory since 2012 and applies to securitizations eligible as collateral in Eurosystem monetary policy operations. The ESMA template, aimed at improving transparency for investors, applies to all public securitizations and has been mandatory since 2021.

Figure 1: Credit market conditions in the Italian provinces.



(a) New loans (EUR) **(b)** Interest rate on loans (%)

Notes. Quantile maps of the new lending volumes (in euro) (panel a) and interest rate on loans (average across maturity terms) (in percent) (panel b) granted to SMEs across Italian NUTS3 provinces. Average value computed over the period 2008Q1–2019Q4.

mortgage-backed securities, consumer loans, leasing, and credit cards. Our empirical analysis focuses on loan-level observations for SMEs.[7]

Following Barbaglia, Manzan, and Tosetti (2023), we use credit market variables at their origination. In particular, our main variables of interest are the amount of loans at origination granted by banks to SMEs and the corresponding interest rate (average across maturity terms) charged by banks on firms' loans. Figure 1 reports quantile maps of the average new loan volumes (panel a) and lending interest rates (panel b) across Italian provinces, computed over the full sample period ($2008Q1 - 2019Q4$). Moreover, we use the loan term (measured in quarters) and the collateral ratio associated with the specific loan. Furthermore, as a proxy for real economic activity, we use data on annual GDP per capita at constant prices at the NUTS3 level downloaded from the ARDECO database. Finally, as a proxy for ex-ante flood risk, we rely on measures of average flood exposure at the NUTS3 (provincial) level. Specifically, we use province-level flood risk indicators

[7] Over the sample period, EDW provides SME loan-level data from ABS issuers located in Belgium, France, Germany, Italy, Luxembourg, the Netherlands, Portugal, and Spain. However, the focus of this paper is exclusively on Italian SMEs.

provided by the "Istituto Superiore per la Protezione e la Ricerca Ambientale" (ISPRA), updated to 2020. These indicators are constructed for alternative flood hazard scenarios, each corresponding to a different probability of flood occurrence: (*i*) a high-probability hazard scenario, capturing frequent flood events; (*ii*) a medium-probability hazard scenario, associated with less frequent floods; and (*iii*) a low-probability hazard scenario, reflecting rare or extreme flood events. For each scenario, the indicator measures the share of the provincial surface area exposed to the corresponding flood risk, expressed as a percentage of the total area of the province. ISPRA provides these measures at different levels of spatial aggregation, including national, regional, provincial, and municipal levels. Our empirical analysis relies on the provincial-level indicators as measures of average flood exposure for each NUTS3 province.[8] The quantile map in Figure 2 shows the average exposure to high flood risk (i.e., the high-probability hazard scenario) for each Italian province.[9] Figure 2 highlights substantial heterogeneity in flood risk across Italian provinces.

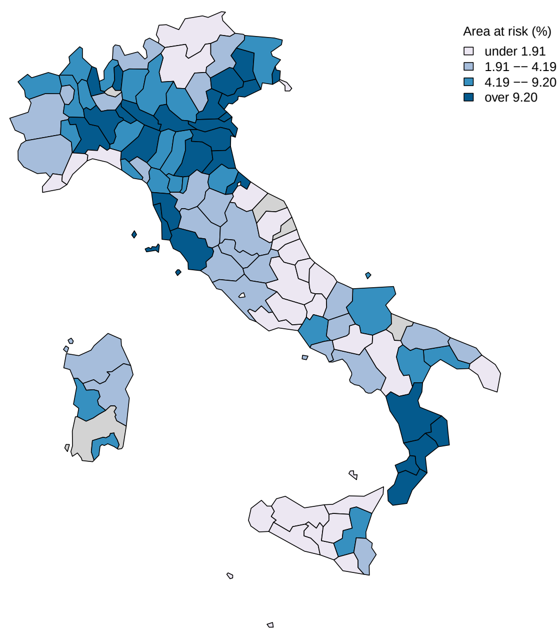
3.2 Empirical evidence

Table 1 reports descriptive statistics for the full sample of 103 NUTS3 provinces (panel a) and for the subsample of Southern Italian provinces (panel b) over the period $2008Q1 - 2019Q4$. As for the credit market conditions, inspection of panels a and b of Table 1 reveals a similar distribution of new loans (measured in logs) across the two groups, with nearly identical means, standard deviations, and percentiles, with the only exception of the upper tail, where the 90^{th} percentile of the distribution is lower in the South (11.95) compared to the national average (12.21). By contrast, non-negligible differences emerge in the distribution of interest rates: the full-sample and Southern-provinces subsample mean values are 4.05 and 4.76 percent, respectively; the full-sample and Southern-provinces subsample 10^{th} percentiles are 1.66 and 2.43 percent, respectively; and the full-sample and Southern-provinces subsample 90^{th} percentiles are 6.50 and 7 percent, respectively. This pattern suggests that, while the volumes of new lending are similar, the cost of credit is higher in Southern Italy. Moreover, as expected, GDP per capita reported by the southern provinces is below the national average across the entire distribution: the average GDP per capita in the southern provinces is equal to 19 338 euro (compared to

[8] Equivalently, the provincial exposure to flood risk can be obtained as the area-weighted average of municipal-level exposures, using total municipal surface area as weights.

[9] Quantile maps for medium and low exposure to flood risk (i.e., corresponding to medium- and low-probability hazard scenarios) are available upon request.

Figure 2: Ex-ante flood risk in the Italian provinces.



Notes. Quantile map of the percentage of the area exposed to flood risk under the high-probability risk scenario (i.e., frequent floods) for each Italian NUTS3. Data updated to 2020.

29 945 euro at the national level); the southern-provinces subsample 10^{th} percentile is 16 140 euro (compared to 18 209 euro at the national level); and the southern-provinces subsample 90^{th} percentile is 24 259 euro (compared to 40 699 euro at the national level). Overall, these statistics suggest that the higher borrowing cost observed in the southern provinces is associated with weaker economic conditions (proxied by GDP per capita), reflecting a higher risk premium incorporated by banks when granting loans to provinces with relatively low GDP per capita.

Table 2 shows descriptive statistics for the full sample of provinces (panel a) and for the subsample of high-flood-risk provinces (panel b), defined as those reporting a value of the proxy for ex-ante flood risk above the median of the empirical distribution.[10] Unlike the comparison between the full sample and the southern provinces, no relevant differences emerge in the distributions of either new loans or lending rates: mean values, standard deviations, and percentiles are similar across the two groups when distinguishing high-

[10] In Table 2, we focus on the percentage of provincial area exposed to high flood risk. Descriptive statistics based on the percentage of the area exposed to medium or low flood risk are available upon request.

Table 1: Descriptive statistics: full sample vs. Southern provinces.

***Panel a*: Full sample**	N	Mean	St. dev.	10th	25th	50th	75th	90th
New loans (log)	240 807	10.73	1.08	9.62	9.94	10.60	11.36	12.21
Interest rate (%)	240 807	4.05	1.13	1.66	2.50	3.95	5.38	6.50
GDP per capita (euro)	240 807	29 945	9 171	18 209	23 680	29 781	33 561	40 699
Loan term (quarters)	240 807	20.24	15.72	8.00	12.00	20.00	20.00	34.00
Collateral ratio	240 807	0.28	1.51	0.00	0.00	0.00	0.00	0.00
High exposure (%)	103	6.04	5.72	0.91	1.73	4.12	9.20	13.65

***Panel b*: Southern provinces**	N	Mean	St. dev.	10th	25th	50th	75th	90th
New loans (log)	56 869	10.68	1.00	9.62	10.00	10.60	11.23	11.95
Interest rate (%)	56 869	4.76	1.85	2.43	3.50	4.75	6.00	7.00
GDP per capita (euro)	56 869	19 338	2 965	16 140	17 642	18 583	20 876	24 259
Loan term (quarters)	56 869	21.53	17.63	8.00	12.00	20.00	20.00	40.00
Collateral ratio	56 869	0.30	1.57	0.00	0.00	0.00	0.00	0.00
High exposure (%)	36	4.64	5.75	0.91	1.22	2.31	4.80	14.70

Notes. Descriptive statistics for the full sample (panel a) and for the provinces located in Southern Italy (panel b). High exposure denotes the share of the provincial surface area exposed to high flood risk, defined as the high-probability flood hazard scenario, relative to the total area of the province. Sample: 2008Q1–2019Q4.

flood-risk provinces from the rest of the sample.

Table 3 reports the estimates of the multivariate static equation model, where the dependent variables are the logarithm of new lending (columns 1 and 3) and the loan interest rate (columns 2 and 4). We present results for two alternative specifications of equation (1). The baseline specification includes the logarithm of provincial GDP per capita as a proxy for local economic activity (columns 1 and 2), while the alternative specification replaces this control with the interaction of province- and time-fixed effects (columns 3 and 4). As shown in Table 3, the estimated coefficients are qualitatively and quantitatively similar across the two specifications. Longer loan maturities are associated with both larger new lending volumes and higher lending rates across all specifications. In the baseline specification (columns 1 and 2), the estimated effects are 0.296 and 0.161, respectively, both statistically significant at the 1% level. The inclusion of province-by-quarter fixed effects yields very similar estimates, with coefficients of 0.284 for new lending and 0.177 for interest rates (columns 3 and 4). A higher collateral ratio is associated with larger new lending volumes and lower lending rates. In the baseline specification, the estimated coefficients are 0.074 and -0.099, respectively, and both are statistically significant at the 1% level (columns 1 and 2). These results are robust to the alternative

Table 2: Descriptive statistics: full sample vs. high flood risk provinces.

***Panel A*: Full sample**	N	Mean	St. dev.	10th	25th	50th	75th	90th
New loans (log)	240 807	10.73	1.08	9.62	9.94	10.60	11.36	12.21
Interest rate (%)	240 807	4.05	1.13	1.66	2.50	3.95	5.38	6.50
GDP per capita (euro)	240 807	29 945	9 171	18 209	23 680	29 781	33 561	40 699
Loan term (quarters)	240 807	20.24	15.72	8.00	12.00	20.00	20.00	34.00
Collateral ratio	240 807	0.28	1.51	0.00	0.00	0.00	0.00	0.00
High exposure (%)	103	6.04	5.72	0.91	1.73	4.12	9.20	13.65

***Panel B*: High flood risk provinces**	N	Mean	St. dev.	10th	25th	50th	75th	90th
New loans (log)	102 145	10.77	1.09	9.62	9.96	10.60	11.51	12.21
Interest rate (%)	102 145	3.83	1.92	1.50	2.40	3.60	5.12	6.35
GDP per capita (euro)	102 145	29 401	5 775	19 182	26 416	30 145	33 164	35 939
Loan term (quarters)	102 145	19.53	14.40	6.00	12.00	20.00	20.00	28.00
Collateral ratio	102 145	0.25	1.33	0.00	0.00	0.00	0.00	0.00
High exposure (%)	51	10.26	5.39	5.03	6.23	9.20	11.96	18.50

Notes. Descriptive statistics for the full sample (panel a) and for provinces with high flood risk exposure (panel b). The latter are defined as provinces with values of the flood risk proxy (i.e., high exposure) above the median of its empirical distribution. High exposure denotes the share of the provincial surface area exposed to high flood risk, defined as the high-probability flood hazard scenario, relative to the total area of the province. Sample: 2008Q1–2019Q4.

specification, which delivers nearly identical estimates for new lending (0.077) and for interest rates (−0.102) (columns 3 and 4). Overall, the estimated effects of both loan maturity and collateral are in line with the evidence reported by Barbaglia, Fatica, and Rho (2023) for European NUTS3 provinces. Moreover, the estimated coefficients on provincial GDP per capita are positive in both equations (0.298 for new loans and 0.500 for interest rates), but they are not statistically significant (columns 1 and 2). Finally, the borrowers dummy, which equals one for firms with repeated loan observations in the sample, has no statistically significant effect on new lending volumes (columns 1 and 3). By contrast, it is associated with lower lending rates, with an estimated coefficient of −0.278 that is statistically significant in both specifications (columns 2 and 4). In the remainder of the paper, we use the baseline specification (columns 1 and 2) as our benchmark specification.[11]

The reduced-form residuals from the baseline specification are then used to identify neg-

[11] The main empirical findings are robust to the alternative specification (columns 3 and 4) and are available upon request.

Table 3: Results from the multivariate static equation model.

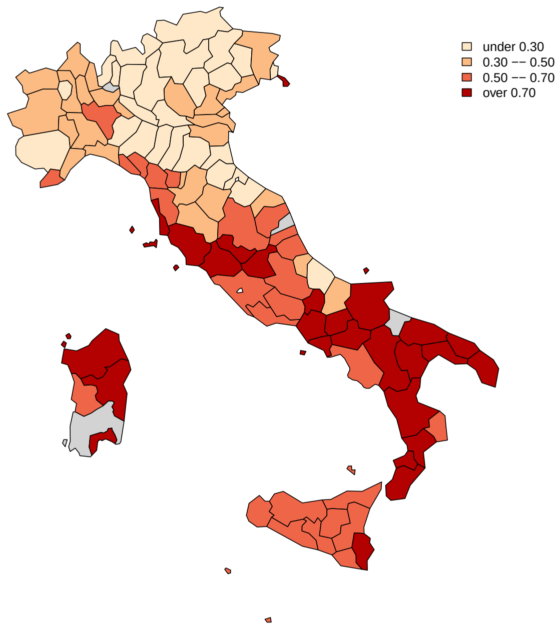
	(1) Log loans	(2) Interest rate	(3) Log loans	(4) Interest rate
Loan term (log)	0.296***	0.161***	0.284***	0.177***
	(0.021)	(0.038)	(0.023)	(0.039)
Collateral ratio	0.074***	-0.099***	0.077***	-0.102***
	(0.010)	(0.008)	(0.011)	(0.008)
GDP per capita (log)	0.298	0.500		
	(0.504)	(1.416)		
Borrowers	0.001	-0.278***	0.001	-0.278***
	(0.014)	(0.018)	(0.012)	(0.017)
Fixed Effects:				
NUTS3	Yes	Yes	No	No
Quarter	Yes	Yes	No	No
NUTS3 × Quarter	No	No	Yes	Yes
Observations	240 807	240 807	240 807	240 807
R^2	0.091	0.334	0.128	0.373

Notes. The dependent variables are the logarithm of new lending (columns 1 and 3) and interest rate on loans (in percent) (columns 2 and 4). Loan term and GDP per capita are taken in logs. Borrowers is a dummy variable equal to one if a firm receives more than one loan, and zero otherwise. Standard errors clustered at the NUTS3 level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation sample: 2008Q1–2019Q4.

ative credit supply shocks at the NUTS3 level. These shocks are subsequently employed to construct the provincial credit supply indicator, as described in Section 2. Figure 3 presents a quantile map of the credit supply indicator (CSI), rescaled to take values between zero and one, across the 103 Italian NUTS3 provinces. As discussed in Section 2, each province is associated with a set of admissible indicators consistent with the theory-driven sign restrictions. For each province, we therefore use the median of the empirical distribution of admissible indicators and classify provinces according to the quantiles of the resulting cross-sectional distribution. Figure 3 reveals a pronounced North-South divide in credit supply conditions, with Southern provinces exhibiting greater credit tightening (i.e., lower lending volumes and higher borrowing costs) than provinces in Central and Northern Italy.

In the second stage of the analysis, we examine the relationship between ex-ante flood risk and the provincial credit supply indicator (CSI). We begin by focusing on the median CSI computed for each province over the full sample period. Table 4 reports estimates from

Figure 3: Distribution of the credit supply indicator across Italian NUTS3 provinces.



Notes.The figure reports the quantile map of the provincial credit supply indicator (CSI). For each province, the CSI is computed as the median of the empirical distribution of admissible indicators obtained from the sign restrictions identification scheme described in Section 2. The CSI is rescaled to take values between 0 and 1, with higher values indicating tighter credit supply conditions. Estimation sample: $2008Q1 - 2019Q4$.

cross-sectional regressions where the main explanatory variables are alternative proxies for flood risk, measured as the share of provincial surface area exposed to high- (column 1), medium- (column 2), and low-probability (column 3) flood hazards. All specifications additionally control for local economic development, proxied by the logarithm of provincial GDP per capita measured at the beginning of the sample period (2008), and include interaction terms between flood risk exposure and GDP per capita.[12] As shown in Table 4, the estimated coefficient on flood risk exposure is positive across all three specifications, suggesting that provinces more exposed to flood hazards tend to exhibit tighter credit supply conditions. A one-percentage-point increase in the share of provincial area exposed to flood risk is associated with an increase in the credit supply indicator of 0.044, 0.085, and 0.181 units under the low-, medium-, and high-probability flood-risk scenarios, respectively. These estimates suggest that the effect of flood risk on credit

[12]GDP per capita is measured at the beginning of the sample period to help mitigate potential endogeneity concerns.

Table 4: Impact of flood risk on the credit supply indicator in Italian provinces.

	(1) High-risk	(2) Medium-risk	(3) Low-risk
Intercept	5.848***	6.105***	6.295***
	(1.127)	(1.007)	(1.037)
High exposure (%)	0.181*		
	(0.108)		
GDP per capita (log)	-0.521***	-0.548***	-0.566***
	(0.112)	(0.099)	(0.103)
High exposure × GDP per capita (log)	-0.018*		
	(0.011)		
Medium exposure (%)		0.085	
		(0.058)	
Medium exposure × GDP per capita (log)		-0.008	
		(0.006)	
Low exposure (%)			0.044
			(0.045)
Low exposure × GDP per capita (log)			-0.004
			(0.004)
Observations	102	103	103
R^2	0.522	0.518	0.514

Notes. The dependent variable is the credit supply indicator (CSI) rescaled to take values between 0 and 1. Each specification uses a different measure of ex-ante flood risk exposure: high (column 1), medium (column 2), and low (column 3). High, medium, and low exposure denote the share of the provincial surface area exposed to high-, medium-, and low-probability flood hazards, respectively, relative to the total provincial area. GDP per capita is expressed in logarithms and measured in 2008. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

supply conditions increases with the severity of the hazard, although statistical significance emerges only for the high-probability flood risk scenario. The interaction between flood risk exposure and GDP per capita is negative across all specifications (-0.018 for high exposure, -0.008 for medium exposure, and -0.004 for low exposure), suggesting that the adverse effect of flood risk exposure on credit supply conditions is mitigated in more economically developed provinces. However, consistent with the main flood-risk coefficient, statistical significance is achieved only under the high-probability flood risk scenario. GDP per capita enters with a negative and statistically significant coefficient across all specifications, indicating that economically more developed provinces tend to exhibit less severe credit supply tightening. Overall, after controlling for differences in

Table 5: Annual cross-sectional estimates of the impact of flood risk exposure on the credit supply indicator.

Panel A: High flood risk exposure

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Intercept	**5.159*****	**6.017*****	**5.921*****	**3.367*****	**3.905*****	**6.359*****	**4.448*****	**5.883*****	**6.126*****	**6.846*****	**7.265*****	**4.973*****
	(1.009)	(1.180)	(1.035)	(0.819)	(1.084)	(0.953)	(0.950)	(1.000)	(1.054)	(0.938)	(1.094)	(1.041)
Exposure (%)	0.109	0.200	0.166	0.081	-0.061	**-0.342****	0.027	0.017	**0.267*****	0.190	**0.236****	**0.301*****
	(0.111)	(0.155)	(0.131)	(0.086)	(0.160)	(0.170)	(0.143)	(0.127)	(0.097)	(0.117)	(0.117)	(0.094)
GDP per capita (log)	**-0.456*****	**-0.548*****	**-0.532*****	**-0.298*****	**-0.325*****	**-0.572*****	**-0.380*****	**-0.523*****	**-0.557*****	**-0.631*****	**-0.668*****	**-0.443*****
	(0.100)	(0.117)	(0.102)	(0.081)	(0.106)	(0.094)	(0.094)	(0.099)	(0.105)	(0.093)	(0.108)	(0.103)
Exposure × GDP per capita (log)	-0.011	-0.020	-0.016	-0.007	0.006	**0.033****	-0.003	-0.002	**-0.026*****	-0.019	**-0.023****	**-0.029*****
	(0.011)	(0.015)	(0.013)	(0.008)	(0.015)	(0.017)	(0.014)	(0.012)	(0.010)	(0.011)	(0.012)	(0.009)
Observations	102	101	101	101	101	102	102	101	102	102	102	102
R^2	0.420	0.459	0.456	0.311	0.215	0.368	0.404	0.515	0.597	0.635	0.558	0.490

Panel B: Medium flood risk exposure

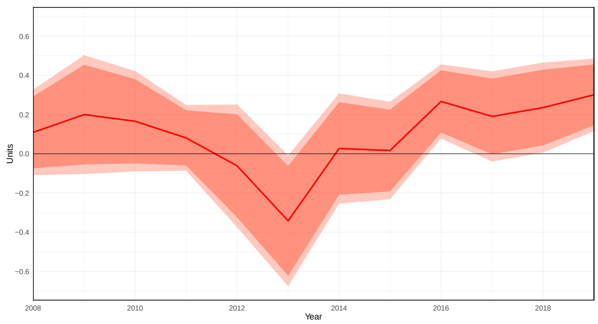
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Intercept	**5.855*****	**7.218*****	**6.698*****	**3.305*****	**4.273*****	**5.706*****	**4.971*****	**6.517*****	**6.975*****	**8.057*****	**8.256*****	**5.837*****
	(0.902)	(1.033)	(0.944)	(0.768)	(1.028)	(0.850)	(0.771)	(0.890)	(0.988)	(0.905)	(1.049)	(0.949)
Exposure (%)	-0.006	-0.029	0.014	0.058	-0.090	**-0.165***	-0.065	-0.066	0.074	-0.005	0.044	**0.111***
	(0.062)	(0.089)	(0.064)	(0.065)	(0.086)	(0.087)	(0.066)	(0.055)	(0.056)	(0.063)	(0.064)	(0.059)
GDP per capita (log)	**-0.524*****	**-0.666*****	**-0.608*****	**-0.290*****	**-0.361*****	**-0.507*****	**-0.432*****	**-0.587*****	**-0.641*****	**-0.752*****	**-0.767*****	**-0.529*****
	(0.089)	(0.102)	(0.093)	(0.075)	(0.100)	(0.084)	(0.076)	(0.088)	(0.098)	(0.089)	(0.103)	(0.094)
Exposure × GDP per capita (log)	0.001	0.003	-0.001	-0.005	0.009	**0.016***	0.006	0.006	-0.007	0.001	-0.004	**-0.011***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Observations	103	102	102	102	102	103	103	102	103	103	103	103
R^2	0.416	0.452	0.450	0.271	0.220	0.334	0.418	0.509	0.581	0.625	0.548	0.474

Panel C: Low flood risk exposure

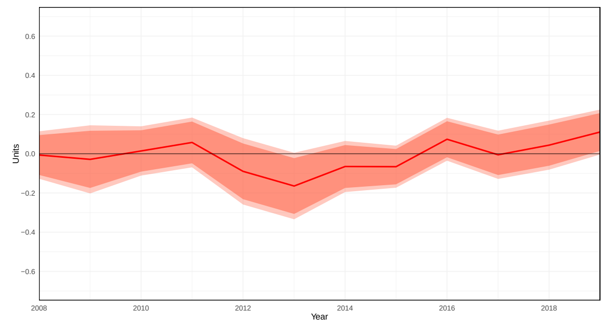
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Intercept	**6.033*****	**7.499*****	**6.779*****	**3.594*****	**4.150*****	**5.192*****	**4.768*****	**6.261*****	**7.409*****	**8.320*****	**8.471*****	**6.274*****
	(0.937)	(1.041)	(0.983)	(0.776)	(1.014)	(1.030)	(0.791)	(0.909)	(1.001)	(0.903)	(1.051)	(0.994)
Exposure (%)	-0.018	-0.059	0.001	0.028	-0.045	-0.062	-0.036	-0.024	0.004	-0.041	-0.010	0.029
	(0.045)	(0.054)	(0.045)	(0.042)	(0.061)	(0.082)	(0.044)	(0.039)	(0.041)	(0.040)	(0.050)	(0.051)
GDP per capita (log)	**-0.542*****	**-0.693*****	**-0.616*****	**-0.319*****	**-0.350*****	**-0.459*****	**-0.412*****	**-0.562*****	**-0.682*****	**-0.777*****	**-0.786*****	**-0.570*****
	(0.093)	(0.103)	(0.097)	(0.077)	(0.099)	(0.101)	(0.078)	(0.090)	(0.099)	(0.089)	(0.104)	(0.098)
Exposure × GDP per capita (log)	0.002	0.006	0.000	-0.003	0.004	0.006	0.003	0.002	0.000	0.004	0.001	-0.003
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	103	102	102	102	102	103	103	102	103	103	103	103
R^2	0.417	0.461	0.450	0.282	0.206	0.289	0.419	0.504	0.579	0.628	0.554	0.461

Notes. Each column reports the estimates from a cross-sectional regression estimated separately for the corresponding year. The dependent variable is the credit supply indicator, rescaled to take values between 0 and 1. Each panel reports estimates based on a different measure of ex-ante flood risk exposure: high (panel a), medium (panel b), and low (panel c). High, medium, and low exposure denote the share of the provincial surface area exposed to high-, medium-, and low-probability flood hazards, respectively, relative to the total provincial area. GDP per capita is expressed in logarithms and measured in 2008. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation sample: 2008 – 2019.

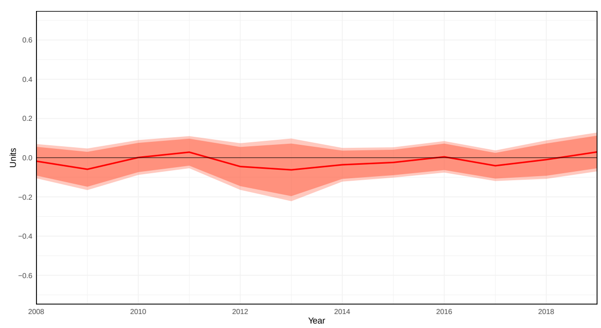
Figure 4: Time-varying impact of ex-ante flood risk exposure on the credit supply indicator in Italian provinces.



(a) High flood risk exposure



(b) Medium flood risk exposure



(c) Low flood risk exposure

Notes. The figure reports the annual estimates of the coefficient on flood risk exposure obtained from the cross-sectional regressions. Panels a, b, and c correspond to the high-, medium-, and low-probability flood-risk scenarios, respectively. The solid red line denotes the estimated coefficient, while the shaded areas represent the 90% and 95% confidence intervals based on heteroskedasticity-robust standard errors. Estimation sample: $2008 - 2019$.

economic development, the full-sample analysis provides only limited evidence that ex-ante flood risk contributes to tighter provincial credit supply conditions, with statistically significant effects emerging only under the high-probability flood risk scenario.

However, the effect of flood risk on credit supply conditions may not be constant over time. We therefore estimate the model separately for each year. While the flood risk measures remain fixed over time, the annual regressions allow us to examine whether their association with the time-varying credit supply indicator changes across years. Table 5 reports the estimated coefficients for the flood risk exposure variables, the interaction terms with GDP per capita, and the GDP coefficient from annual cross-sectional regressions estimated separately for each year over the period 2008–2019. The dependent variable is the normalized credit supply indicator, constructed using information on new lending volumes and borrowing costs observed in each year. The table is organized into three panels corresponding to the alternative flood hazard scenarios: Panel a reports the results for the high-probability scenario, Panel b for the medium-probability scenario, and Panel c for the low-probability scenario. GDP per capita enters with a negative and statistically significant coefficient across all years and hazard scenarios, indicating that SMEs located in economically more developed provinces consistently experience less severe credit supply tightening. The magnitude of the coefficients ranges between -0.786 and -0.290 (see panels a, b, and c of Table 5). This result confirms that local economic development is an important determinant of cross-provincial differences in credit supply conditions. Turning to flood risk exposure, the results for the high-probability flood scenario indicate a positive and statistically significant effect (at the 95% confidence level) of flood risk exposure on credit supply tightening, particularly during the latter part of the sample. Specifically, from 2016 onward, the coefficient on flood risk exposure is positive and statistically significant (the only exception is the 2017), with an average value of 0.248 over the $2016-2019$ period (see Panel a of Table 5). In the same years (2016, 2018, and 2019), the interaction between flood risk exposure and GDP per capita is negative and statistically significant, suggesting that the positive association between high flood risk exposure and credit supply tightening is weaker in economically more developed provinces. By contrast, under the medium-probability flood scenario, a positive and statistically significant effect (at 90% level of confidence) of flood risk exposure is observed only in 2019, while no statistically significant effects are found under the low-probability scenario (see Table 5, panels b and c). Figure 4 reports the time-varying estimates of the coefficient on flood risk exposure over the period $2008-2019$. Results are shown separately for the high-, medium-, and low-probability flood risk scenarios in panels a, b, and c, respectively. In each panel, the solid red line represents the estimated coefficient, while the shaded area denotes the 95% and 90% confidence intervals based on heteroskedasticity-robust standard errors. Figure 4 provides a graphical representation of the results reported in Table 5, focusing exclusively on the coefficient measuring the effect of flood risk exposure on the normalized credit supply indicator. The estimated coefficient under the high-probability flood scenario is positive and statistically significant (at the 95% confidence level) from 2016 onward, with the only exception of 2017 (see panel a). Under the medium-probability flood scenario, the estimated effect is smaller in magnitude and reaches statistical significance (at the 90% confidence level) only in the final year of the sample (see panel b). Finally, under the low-probability flood scenario, the estimated coefficient is not statistically different from

Table 6: Results from the multivariate static equation model: including COVID-19.

	(1) **Log loans**	**(2)** **Interest rate**	**(3)** **Log loans**	**(4)** **Interest rate**
Loan term (log)	0.172***	0.075**	0.217***	0.115***
	(0.027)	(0.033)	(0.023)	(0.033)
Collateral ratio	0.090***	-0.087***	0.086***	-0.094***
	(0.011)	(0.007)	(0.012)	(0.007)
GDP per capita (log)	-0.111	0.899		
	(0.910)	(1.068)		
Borrowers	0.106***	-0.105***	0.073***	-0.136***
	(0.020)	(0.018)	(0.013)	(0.017)
Fixed Effects:				
NUTS3	Yes	Yes	No	No
Quarter	Yes	Yes	No	No
NUTS3 × Quarter	No	No	Yes	Yes
Observations	337 388	337 388	337 388	337 388
R^2	0.120	0.516	0.200	0.556

Notes. The dependent variables are the logarithm of new lending (columns 1 and 3) and interest rate on loans (in percent) (columns 2 and 4). Loan term and GDP per capita are taken in logs. Borrowers is a dummy variable equal to one if a firm receives more than one loan, and zero otherwise. Standard errors clustered at the NUTS3 level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation sample: $2008Q1 - 2021Q2$.

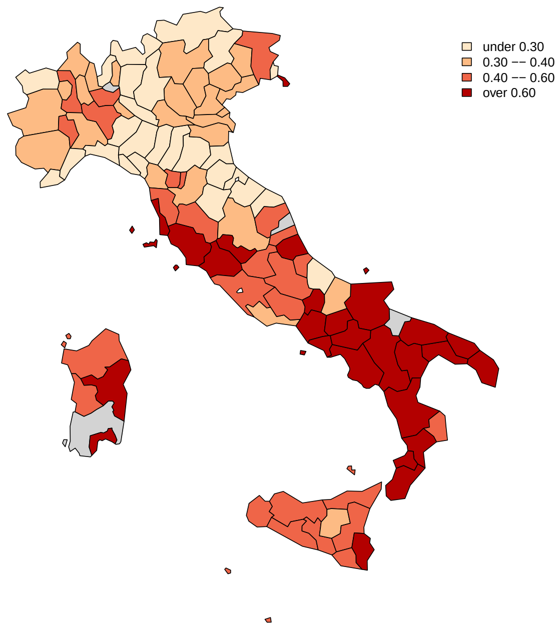
zero throughout the sample period (see panel c).

4 Including COVID-19 observations

In this section, we extend the estimation sample to include the COVID-19 period. Specifically, we re-estimate the model in equation (1) using quarterly data over the period $2008Q1 - 2021Q2$. The results from the estimation of the multivariate static equation model are reported in Table 6. Consistent with the baseline analysis over $2008Q1 - 2019Q4$, we report results for two alternative specifications. The first includes provincial GDP per capita among the regressors (columns 1 and 2), while the second replaces GDP per capita with province–time fixed-effects interactions (columns 3 and 4). Comparing Tables 3 and 6 shows that the first-stage estimates remain both qualitatively and quantitatively similar after extending the sample to include the COVID-19 period.

The residuals from equation (1), estimated over the period $2008Q1 - 2021Q2$, are then

Figure 5: Distribution of the credit supply indicator across Italian NUTS3 provinces: including COVID-19.



Notes. The figure reports the quantile map of the provincial credit supply indicator (CSI). The indicator is rescaled to take values between 0 and 1, with higher values indicating tighter credit supply conditions. For further details on the construction of the CSI, see Section 2. Estimation sample: $2008Q1 - 2021Q2$.

used to, first, construct the provincial credit supply indicator and, then, to reassess both the average and the time-varying contribution of ex-ante flood risk to provincial credit supply conditions (see Section 2). Figure 5 shows the quantile map of the credit supply indicator at the provincial level. Consistent with the baseline results, the inclusion of the COVID-19 period does not alter the spatial pattern of credit supply conditions, with Southern provinces exhibiting higher levels of credit constraints than provinces in Central and Northern Italy on average over the $2008Q1 - 2021Q2$ period. Finally, Table 7 reports the average cross-sectional regression estimates of the effect of flood risk exposure on credit supply, while Table 8 and Figure 6 present the corresponding annual (time-varying) cross-sectional estimates. Overall, the results remain qualitatively and quantitatively similar to those discussed in Section 3.2, indicating that the main conclusions are robust to the inclusion of the COVID-19 period. Consistent with the baseline specification, provinces with greater exposure to flood risk exhibit tighter credit supply conditions, with more pronounced effects observed in provinces with lower GDP per

Table 7: Impact of flood risk on the credit supply indicator in Italian provinces: including COVID-19.

	(1) High-risk	(2) Medium-risk	(3) Low-risk
Intercept	5.505***	5.502***	6.013***
	(1.258)	(1.151)	(1.183)
High exposure (%)	0.189*		
	(0.109)		
GDP per capita (log)	-0.495***	-0.496***	-0.545***
	(0.124)	(0.113)	(0.117)
High exposure × GDP per capita (log)	-0.019*		
	(0.011)		
Medium exposure (%)		0.131*	
		(0.067)	
Medium exposure × GDP per capita (log)		-0.013*	
		(0.007)	
Low exposure (%)			0.058
			(0.053)
Low exposure × GDP per capita (log)			-0.006
			(0.005)
Observations	102	103	103
R^2	0.426	0.433	0.422

Notes. The dependent variable is the credit supply indicator (CSI) rescaled to take values between 0 and 1. Each specification uses a different measure of ex-ante flood risk exposure: high (column 1), medium (column 2), and low (column 3). High, medium, and low exposure denote the share of the provincial surface area exposed to high-, medium-, and low-probability flood hazards, respectively, relative to the total provincial area. GDP per capita is expressed in logarithms and measured in 2008. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

capita. However, relative to the baseline results (i.e., $2008Q1-2019Q4$), the evidence becomes somewhat stronger. In particular, the average cross-sectional regressions reported in Table 7 indicate a positive and statistically significant association not only under the high-probability flood-risk scenario but also under the medium-probability scenario. The annual cross-sectional estimates reported in Table 8 and Figure 6 continue to show that the relationship is primarily driven by the latter part of the sample, with statistically significant effects emerging from 2016 onward under the high-probability flood risk scenario and in 2019 under the medium-probability scenario.

Table 8: Annual cross-sectional estimates of the impact of flood risk exposure on CSI: including COVID-19.

Panel A: High flood risk exposure

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Intercept	**4.984*****	**5.249*****	**5.734*****	**4.086*****	**4.019*****	**6.720*****	**4.549*****	**6.157*****	**5.655*****	**6.593*****	**7.103*****	**4.849*****	0.980
	(1.026)	(0.970)	(1.027)	(1.016)	(1.102)	(0.962)	(0.958)	(1.075)	(1.031)	(0.977)	(1.155)	(1.068)	(0.919)
Exposure (%)	0.151	0.189	0.175	0.133	-0.056	**-0.345***	0.051	0.045	**0.276*****	**0.210***	**0.255****	**0.315*****	0.130
	(0.099)	(0.128)	(0.119)	(0.094)	(0.156)	(0.176)	(0.146)	(0.131)	(0.097)	(0.118)	(0.111)	(0.091)	(0.135)
GDP per capita (log)	**-0.439*****	**-0.465*****	**-0.514*****	**-0.362*****	**-0.336*****	**-0.608*****	**-0.392*****	**-0.548*****	**-0.515*****	**-0.605*****	**-0.655*****	**-0.435*****	-0.078
	(0.102)	(0.096)	(0.102)	(0.100)	(0.107)	(0.095)	(0.095)	(0.106)	(0.102)	(0.097)	(0.114)	(0.106)	(0.090)
Exposure × GDP per capita (log)	-0.015	-0.019	-0.017	-0.012	0.005	**0.033***	-0.005	-0.005	**-0.027*****	**-0.021***	**-0.025****	**-0.031*****	-0.013
	(0.010)	(0.012)	(0.012)	(0.009)	(0.015)	(0.017)	(0.014)	(0.013)	(0.010)	(0.012)	(0.011)	(0.009)	(0.013)
Observations	102	101	101	101	101	102	102	101	102	102	102	102	102
R^2	0.418	0.451	0.450	0.342	0.221	0.382	0.428	0.518	0.595	0.624	0.564	0.498	0.055

Panel B: Medium flood risk exposure

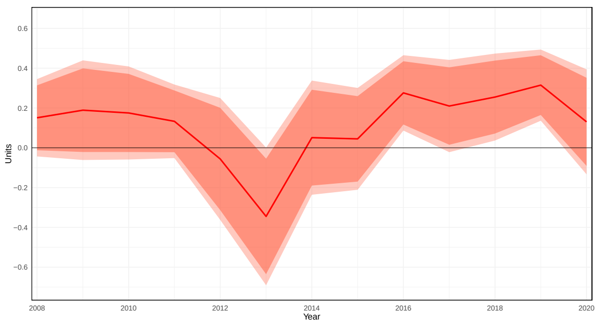
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Intercept	**5.573*****	**6.144*****	**6.363*****	**4.028*****	**4.332*****	**5.992*****	**5.074*****	**6.798*****	**6.447*****	**7.752*****	**8.056*****	**5.675*****	1.396
	(0.965)	(0.867)	(0.955)	(0.945)	(1.060)	(0.870)	(0.789)	(0.971)	(0.964)	(0.942)	(1.105)	(0.975)	(0.855)
Exposure (%)	0.042	0.011	0.045	0.097	-0.076	**-0.154***	-0.046	-0.044	0.091	0.016	0.066	**0.127****	0.024
	(0.067)	(0.078)	(0.063)	(0.068)	(0.089)	(0.092)	(0.068)	(0.060)	(0.055)	(0.065)	(0.066)	(0.059)	(0.066)
GDP per capita (log)	**-0.497*****	**-0.554*****	**-0.577*****	**-0.354*****	**-0.368*****	**-0.537*****	**-0.444*****	**-0.613*****	**-0.593*****	**-0.721*****	**-0.751*****	**-0.517*****	-0.119
	(0.095)	(0.086)	(0.094)	(0.093)	(0.103)	(0.085)	(0.078)	(0.096)	(0.095)	(0.093)	(0.109)	(0.096)	(0.083)
Exposure × GDP per capita (log)	-0.004	-0.001	-0.004	-0.009	0.007	**0.015***	0.004	0.004	-0.009	-0.002	-0.006	**-0.012****	-0.002
	(0.006)	(0.008)	(0.006)	(0.006)	(0.009)	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	103	102	102	102	102	103	103	102	103	103	103	103	103
R^2	0.410	0.442	0.445	0.307	0.223	0.346	0.438	0.511	0.578	0.612	0.554	0.481	0.052

Panel C: Low flood risk exposure

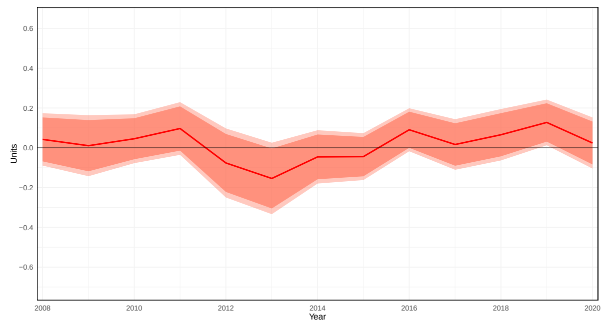
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Intercept	**5.995*****	**6.549*****	**6.622*****	**4.546*****	**4.290*****	**5.563*****	**4.979*****	**6.654*****	**6.950*****	**8.096*****	**8.382*****	**6.193*****	1.264
	(0.995)	(0.880)	(1.001)	(0.973)	(1.041)	(1.036)	(0.802)	(0.985)	(0.992)	(0.950)	(1.120)	(1.029)	(0.857)
Exposure (%)	0.001	-0.036	0.011	0.041	-0.041	-0.059	-0.030	-0.017	0.013	-0.030	-0.001	0.036	0.024
	(0.049)	(0.049)	(0.045)	(0.045)	(0.062)	(0.084)	(0.044)	(0.043)	(0.042)	(0.042)	(0.054)	(0.052)	(0.041)
GDP per capita (log)	**-0.539*****	**-0.593*****	**-0.602*****	**-0.405*****	**-0.365*****	**-0.497*****	**-0.435*****	**-0.599*****	**-0.641*****	**-0.754*****	**-0.780*****	**-0.566*****	-0.105
	(0.098)	(0.087)	(0.099)	(0.096)	(0.101)	(0.102)	(0.079)	(0.097)	(0.098)	(0.094)	(0.110)	(0.102)	(0.084)
Exposure × GDP per capita (log)	0.000	0.003	-0.001	-0.004	0.004	0.006	0.003	0.002	-0.001	0.003	0.000	-0.004	-0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Observations	103	102	102	102	102	103	103	102	103	103	103	103	103
R^2	0.412	0.446	0.443	0.317	0.214	0.308	0.438	0.508	0.571	0.613	0.555	0.464	0.057

Notes. Each column reports the estimates from a cross-sectional regression estimated separately for the corresponding year. The dependent variable is the credit supply indicator, rescaled to take values between 0 and 1. Each panel reports estimates based on a different measure of ex-ante flood risk exposure: high (panel a), medium (panel b), and low (panel c). High, medium, and low exposure denote the share of the provincial surface area exposed to high-, medium-, and low-probability flood hazards, respectively, relative to the total provincial area. GDP per capita is expressed in logarithms and measured in 2008. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation sample: $2008 - 2020$.

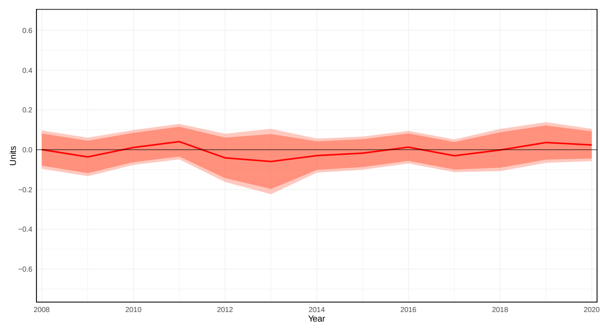
Figure 6: Time-varying impact of ex-ante flood risk exposure on the credit supply indicator in Italian provinces: including COVID-19.



(a) High flood risk exposure



(b) Medium flood risk exposure



(c) Low flood risk exposure

Notes. The figure reports the annual estimates of the coefficient on flood risk exposure obtained from the cross-sectional regressions. Panels a, b, and c correspond to the high-, medium-, and low-probability flood-risk scenarios, respectively. The solid red line denotes the estimated coefficient, while the shaded areas represent the 90% and 95% confidence intervals based on heteroskedasticity-robust standard errors. Estimation sample: $2008 - 2020$.

5 Conclusion

In this study, we analyze the relationship between flood risk exposure and access to bank credit for Italian small and medium-sized enterprises (SMEs). We contribute to the existing literature by constructing a province-level (NUTS3) indicator of credit supply tightening based on loan-level data from the European Datawarehouse. The indicator is based on the identification of negative credit supply shocks through theory-driven sign restrictions using granular information on new lending volumes and interest rates. In the second stage of the analysis, we assess the role played by ex-ante flood risk exposure in shaping provincial credit market conditions. The empirical evidence points to a credit crunch that largely affects Southern provinces. Furthermore, we find that the province-specific average level of flood risk exposure has a detrimental effect on local credit supply, especially in less economically developed areas, but statistical significance is limited to the high-risk scenario. Finally, we find that the contribution of flood risk exposure to credit supply tightening becomes more pronounced in the last part of the sample. In particular, from 2016 onward, a period characterized by increased awareness of climate-related risks, flood risk exposure plays a non-negligible role in shaping credit supply conditions under the high-risk scenario and, to a lesser extent, under the medium-risk scenario. These findings have important policy implications regarding the identification of geographical areas that should be targeted by interventions, such as SME loan guarantees, to mitigate the impact of flood risk on the contraction of credit supply.

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Appendices

Appendix A. EDW data for Italian SMEs

This appendix describes the procedures followed to construct the loan-level dataset for small and medium-sized enterprises (SMEs) located in Italian provinces.[13] We obtain loan-level data (LLD) from the European DataWarehouse (EDW), focusing on all public asset-backed securities (ABS) transactions for Italian SMEs. The EDW database collects granular information on securitized loans and provides a sequence of submissions for each ABS transaction. Each submission is uniquely identified by an *EDCode*, which identifies the securitization deal, and a *Pool Cut-off Date* (PCD), which refers to the reference date for the reported loan-level information. The EDW dataset distinguishes between static and dynamic loan-level variables. Static variables are observed at loan origination and remain constant over time, while dynamic variables are updated at each reporting date and capture the evolution of loan characteristics over time.

To construct the final dataset, we extract a set of static and dynamic variables from the EDW database. Specifically, the static variables retained in our analysis include: (*i*) *Pool Identifier*, the unique identifier of the securitization pool; (*ii*) *Loan Identifier*, the unique identifier assigned to each loan within the pool; (*iii*) *Originator*, the financial institution that originated the loan; (*iv*) *Borrower Identifier*, the unique identifier assigned to each borrower; (*v*) *Geographic Region*, the NUTS3 region in which the borrower is located; (*vi*) *Original Loan Balance*, the total loan amount at origination, expressed in euros; (*vii*) *Loan Origination Date* the date on which the loan is advanced; (*viii*) *Final Maturity Date*, the contractual final maturity date of the loan; (*ix*) *Original Collateral Valuation Amount*, the value of collateral pledged at the time of the latest loan advance prior to securitization. The dynamic variables include: (*i*) *Pool Cut-off Date*; (*ii*) *Current Balance*, the outstanding loan amount as of the pool cut-off date; (*iii*) *Current Interest Rate*, expressed in percent; (*iv*) *Interest Rate Type*, indicating whether the interest rate is fixed, floating, capped, or subject to other contractual arrangements; and (*v*) *Default*, indicating whether the loan has entered default or foreclosure.

We clean the dataset in several ways. First, we restrict the sample to securitization transactions related to Italian SMEs by removing all non-Italian deals, identified using the *Pool Identifier*. We then remove observations with a non-positive outstanding loan

[13] In Italy, the provincial level corresponds to the lowest level of territorial classification under the Nomenclature of Territorial Units for Statistics (NUTS), namely NUTS3.

amount (*Current Balance*), and we drop loans with missing information on the NUTS3 geographical code. Next, we restrict the temporal coverage of the data. We retain loan observations with a *Pool Cut-off Date* between 2013Q1 and 2021Q2, and we keep only loans originated from 2008Q1 onward. Because information reported at loan origination may vary across different pool cut-off dates, we eliminate duplicate loan records by retaining only loans that are uniquely identified by the combination of *Loan Origination Date*, *Original Loan Balance*, *Originator*, and *Borrower Identifier*. In addition, we remove loans displaying missing or repeated pool cut-off dates. We further remove loans with implausible values for the *Final Maturity Date*. We also restrict the sample to loans with fixed or floating interest rates. For floating-rate loans, since our analysis focuses on loan characteristics at origination while interest rates are observed at the pool cut-off date, we retain only loans for which the time difference between the loan origination date and the pool cut-off date does not exceed one year. Moreover, we exclude loans that are in default. Finally, we compute the collateral ratio as the ratio between the *Original Collateral Valuation Amount* and the *Original Loan Balance*. We retain only loans associated with plausible values of the collateral ratio, defined as values below 50.