FIRMS' BORROWING COSTS AND NEIGHBORS' FLOOD RISK

ELECTRONIC SUPPLEMENTARY MATERIAL AVAILABLE ONLINE

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This electronic supplementary material (ESM) provides additional robustness checks for the analyses and conclusions reported in the article "*FIRMS' BORROWING COSTS AND NEIGHBORS' FLOOD RISK*".

A. ADDITIONAL INFORMATION

This section provides additional information regarding the sample construction. Our sample selection process begins with all Italian firms covered by Orbis during the period 2016–2019. From the initial dataset, we deleted observations related to companies with fiscal years shorter than 12 months, missing or negative equity, consolidated accounts, financial institutions, and missing municipality information (i.e., longitude and latitude). The procedure for selecting our final sample is described in Table A1.

Table A1. Sample selection

2,136,506	Firm-year observations (no financial firms) available in ORBIS during 2016-2019, with the fiscal year closing in December, no negative (or missing) book value of equity/assets/sales, and with latitude and longitude information available.
***N.* observations dropped**	**Reason for dropping**
1,238,384	Missing accounting data.
53,264	Interest paid higher than financing liabilities.
109,840	Missing flood risk data.
315,842	Companies with no – at least – 4 years of data.
136	Missing geographical data.
419,040	***Final sample N=104,760 firms, T = 2016-2019.***

Table A2 shows the distribution of observations across industries and years. The most significant observations are in manufacturing, wholesale, and retail trade, followed by construction, real estate, accommodation, and food service activities. Education, utilities, and mining sectors exhibited the lowest number of observations.

Table A2. Sample distribution by year and industry (NACE Code)

NACE Categories	**2016**	**2017**	**2018**	**2019**	***Total***
Accommodation and food service activities	5,530	5,530	5,530	5,530	*22,120*
Administrative and support service activities	3,766	3,766	3,766	3,766	*15,064*
Agriculture, forestry and fishing	1,694	1,694	1,694	1,694	*6,776*
Arts, entertainment and recreation	1,004	1,004	1,004	1,004	*4,016*
Construction	12,325	12,325	12,325	12,325	*49,300*
Education	468	468	468	468	*1,872*
Electricity, gas, steam and air conditioning supply	897	897	897	897	*3,588*
Human health and social work activities	2,505	2,505	2,505	2,505	*10,020*
Information and communication	3,757	3,757	3,757	3,757	*15,028*
Manufacturing	28,200	28,200	28,200	28,200	*112,800*
Mining and quarrying	310	310	310	310	*1,240*
Other service activities	821	821	821	821	*3,284*
Professional, scientific and technical activities	4,732	4,732	4,732	4,732	*18,928*
Public administration and defense	1	1	1	1	*4*
Real estate activities	6,886	6,886	6,886	6,886	*27,544*
Transportation and storage	4,504	4,504	4,504	4,504	*18,016*
Water supply; sewerage, waste management and remediation activities	1,214	1,214	1,214	1,214	*4,856*
Wholesale and retail trade; repair of motor vehicles and motorcycles	26,146	26,146	26,146	26,146	*104,584*
Total	*104,760*	*104,760*	*104,760*	*104,760*	*419,040*

Table A3 reports Pearson's pairwise correlation coefficients. As shown, there was a positive correlation between cost of debt and all the measures of flood risk (coefficients between 3.6% and 6.5%, significant at 1%). However, the results from univariate analysis cannot be generalized since they may be affected by correlated omitted variables.

Table A3. Pearson's correlation coefficients

		1	2	3	4	5	6	7
KD	1	1						
FRarea	2	0.036***	1					
FRpop	3	0.048***	0.827***	1				
FR	4	0.044***	0.956***	0.956***	1			
FR (10km)	5	0.057***	0.775***	0.744***	0.794***	1		
DFR (10km)	6	0.001	-0.572***	-0.612***	-0.619***	-0.015***	1	
ROA	7	0.105***	-0.016***	-0.010***	-0.014***	-0.018***	-0.001	1
TA	8	-0.199***	0.023***	0.012***	0.019***	0.020***	-0.004***	-0.130***
LEV	9	-0.370***	-0.011***	-0.021***	-0.017***	-0.024***	-0.003*	-0.150***
IC	10	-0.117***	-0.024***	-0.021***	-0.023***	-0.032***	-0.004**	0.573***
WC	11	0.056***	-0.020***	-0.016***	-0.019***	-0.020***	0.005***	0.238***
SIZE	12	-0.290***	-0.026***	-0.023***	-0.026***	-0.034***	-0.002	-0.157***
IND_R	13	-0.062***	0.016***	0.016***	0.016***	0.013***	-0.010***	-0.043***

continues…

		8	9	10	11	12	13
TA	8	1					
LEV	9	0.204***	1				
IC	10	-0.112***	-0.381***	1			
WC	11	-0.518***	-0.246***	0.278***	1		
SIZE	12	0.202***	0.105***	0.023***	-0.070***	1	
IND_R	13	0.128***	0.077***	-0.031***	-0.075***	0.123***	1

*Notes. N. Obs. 419,040. *, ** and *** indicate statistical significance at the 0.1, 0.05 and 0.01 levels (two-tailed), respectively.*

In Table A4, we decomposed the spatially lagged difference in volatility into within-variability and between-variability. Considering our 4,215 municipalities as units of observation, we can state that the spatially lagged difference in flood risk exhibited sufficient intra-municipality variability to provide meaningful estimates even when we included municipality fixed effects.

Table A4. Volatility of the spatially lagged difference within and between municipalities

	Variability	Mean	Std. dev.	Min	Max
DFR (10 km)	overall	-0.001	0.563	-3.775	3.083
	between		0.784	-3.695	2.874
	within		0.091	-2.467	3.029

Notes. These statistics are based on 419,040 observations coming from 4,215 municipalities with an average number of firms equal to 99.416.

By providing a quantile-quantile plot between FR_i and $FR_{j \in N_i}$, Figure A1 supports the existence of sufficient local volatility in the flood risk measure.

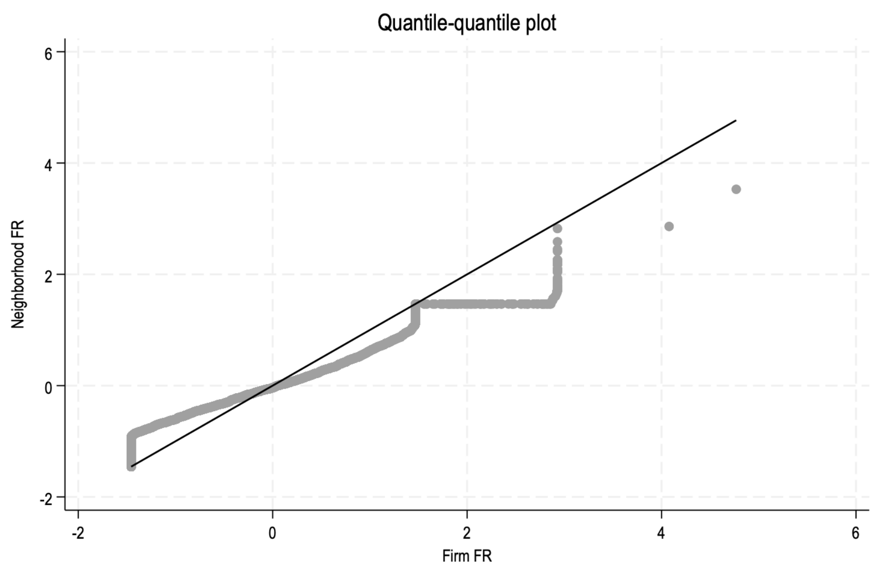

Figure A1. Quantile-quantile plot showing the relative distribution of neighborhood *FR* given firm *FR*.

Figure A2 displays the kernel density function of firms' SIZE divided into two groups: those surrounded by a safer neighborhood in terms of flood risk and those surrounded by a riskier neighborhood. Thus, it is possible to compare the two groups in Figure 4 since their distributions overlap.

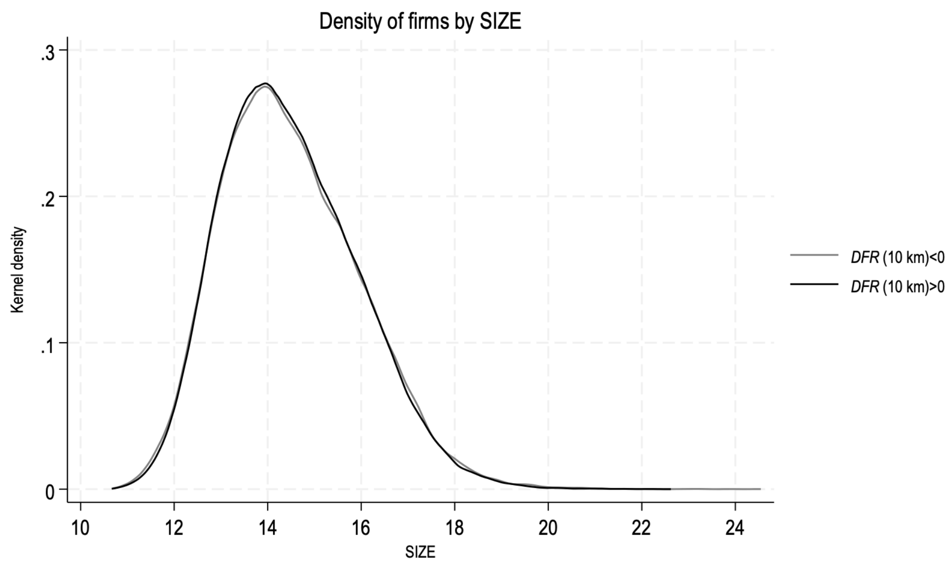

Figure A2. Kernel density estimation of firms' SIZE divided into those surrounded by a safer neighborhood in terms of flood risk and those surrounded by a riskier neighborhood.

Figure A3 displays the kernel density function of firms' SIZE by NUTS1 regions. The distribution of firms located in the northern region of Italy is slightly less concentrated toward small firms than the distribution found in the southern region.

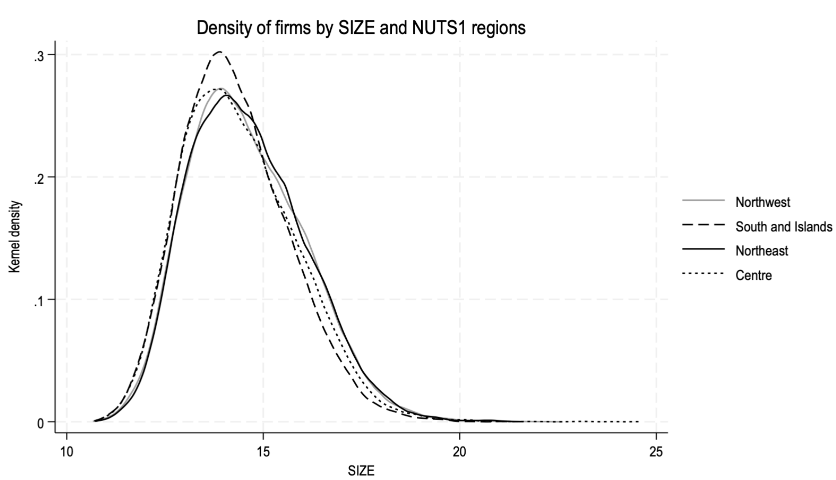

Figure A3. Kernel density estimation of firms' SIZE by NUTS1 regions.

Figure A4 illustrates the distribution of firms' SIZE by NACE 1-digit industries. The largest firms are generally more likely to be involved in industries such as utility supply, real estate, and waste management.

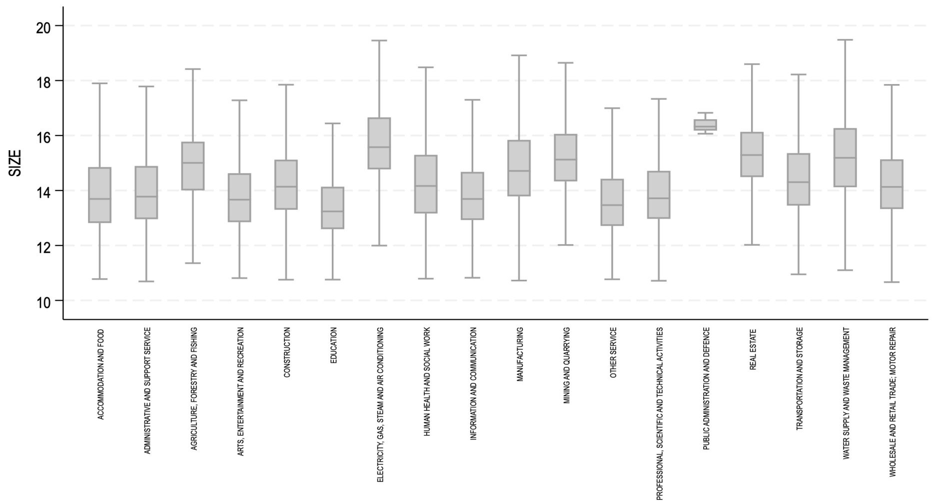

Figure A4. Distribution of firms’ SIZE by NACE 1-digit industries.

B. ESTIMATION STRATEGY AND OMITTED VARIABLES

This section more deeply depicts the key econometric features of our estimation strategy. In particular, we illustrate why our approach is less susceptible to omitted variable problems than a spatial cross-regressive approach in which the neighborhood's flood risk directly enters the model. Suppose that borrowing costs are characterized by the following spatial cross-regressive model:

$$KD_{it} \;=\; \beta_0 FR_i + \beta_2 \overline{FR}_{N_i} + \gamma' X_{it} + \delta Z + \varepsilon_{it}, \tag{B1}$$

where FR_i is the flood risk faced by firm i, $\overline{FR}_{N_i}$ is the average flood risk of firms located in a neighborhood of focal firm i, X_{it} is the set of observed control variables (including a constant term) and Z is an omitted variable that can be correlated with our flood risk indicators (i.e., FR_i and $\overline{FR}_{N_i}$).[1] For example, the unobserved characteristic of a firm might motivate it to locate in a neighborhood with similar neighbors; otherwise, living in a particular neighborhood might facilitate the acquisition of a particular characteristic. In these cases, the omission of Z leads to biased estimates of β.

Now, considering that $\overline{FR}_{j\in N_i} = FR_i + \overline{DFR}_{N_i}$, we can re-write Equation (B1) as follows:

$$KD_{it} = \beta_1 FR_i + \beta_2 \overline{DFR}_{N_i} + \gamma' X_{it} + \delta Z + \varepsilon_{it}, \tag{B2}$$

with $\beta_1 \equiv \beta_0 + \beta_2$.[2] As argued by Grinblatt et al. (2008) and Katicha and Flintsch (2022), similar transformations have the advantage of preserving the linear model structure by radically altering the correlation structure between variables. In particular, if the correlation between Z and $\overline{DFR}_{N_i}$ is weaker than the correlation between Z and $\overline{FR}_{N_i}$, estimating Equation (B2) (without Z) instead of (B1) (without Z) can mitigate the bias due to omitted variables.

Moreover, given Equation (B1), and recalling that FR_i is measured at the municipality level, we can write the average cost of debt paid by firms belonging to the same municipality of firm *i*:

$$KD_{m_i} \;=\; \beta_1 FR_i + \beta_2 \overline{\mathrm{FR}}_{N_{m_i}} + \gamma' X_{m_i} + \delta Z_{m_i} + \varepsilon_{m_i}, \tag{B3}$$

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[1] Without loss of generality, we assume that X_{it} and Z are uncorrelated. However, in the case of correlation, it would be sufficient to modify the coefficient of X_{it} by the coefficient obtained from projecting Z onto X_{it} and replacing Z with the orthogonal component of the projection.

[2] Since our flood risk indicator is measured at the municipality level, if $\overline{DFR}_{N_i} = 0$, then 1 captures the average direct effect of a municipality's flood risk on *KD* of firms located within the same municipality of firm *i*. In contrast, Equation (B1) will suffer from perfect collinearity in this case.

where subscript m_i denotes the average of the variable across time for all firms belonging to the same municipality of firm i.

Thus, considering that $\overline{FR}_{N_{m_i}} = FR_i + \overline{DFR}_{N_{m_i}}$, we can write the difference between Equation (B1) and (B3) as follows:

$$KD_{it} - KD_{m_i} = \beta_2 \left(\overline{DFR}_{N_i} - \overline{DFR}_{N_{m_i}} \right) + \gamma'(X_{it} - X_{m_i}) + \delta(Z - Z_{m_i}) + \varepsilon_{it} - \varepsilon_{m_i}. \quad \text{(B4)}$$

Equation (B4), without $(Z - Z_{m_i})$, represents the within transformation implied by the inclusion of municipality fixed effects into Equation (2) in the article.[3] Therefore, omitting Z and estimating β_2 from Equation (B1) would potentially imply the following bias:

$$\varDelta_{\beta_2} = \delta \, \frac{cov\left(Z, \overline{FR}_{N_i}\right)}{var\left(\overline{FR}_{N_i}\right)}.$$

In contrast, the potential bias of estimating (B4) without $(Z - Z_{m_i})$ would be:

$$\varDelta_{\beta_2} = \delta \, \frac{cov(\varDelta Z, \varDelta DFR)}{var(\varDelta DFR)},$$

with $\varDelta Z \equiv Z - Z_{m_i}$ and $\varDelta DFR \equiv \overline{DFR}_{N_i} - \overline{DFR}_{N_{m_i}}$. Now, if Z is an omitted variable at the municipality level, our within transformation will certainly solve the problem, since $\varDelta Z$ will be zero. Nonetheless, even if Z is correlated with $\overline{DFR}_{N_i}$, by considering the correlation between two differences $\varDelta Z$ and $\varDelta DFR$, we can reasonably expect to mitigate the omitted variable bias. Using Katicha and Flintsch's (2022) words, we may say that: "this decorrelation effect is the key idea in applying differencing or any linear transformation before estimating the model parameters" (p. 4).

[3] With respect to (B2), (B4) is equivalent to a cross-regressive model with municipality fixed effects.

C. Spatial effects and nearest neighbors

In this section, we further test our identification strategy by exploiting the idea behind the nearest neighborhood method discussed in Grinblatt et al. (2008). Indeed, if local spatial effects exist, they should vanish as the distance from the focal firm increases. Using a more compact notation, we could re-write our model as follows:

$$KD \;=\; \beta\, FR + \gamma' X + \delta Z, \tag{C1}$$

where FR is the neighborhood state vector, X is a vector of observed covariates and Z is a vector of unobserved attributes. We can divide FR into two components: $FR = FR_1 + FR_2$, such that:

$$KD \;=\; \beta_1 FR_1 + \beta_2 FR_2 + \gamma' X + \delta Z. \tag{C2}$$

In our case, FR_1 and FR_2 represent the flood risk of two contiguous rings: an inner ring consisting of neighbors located within a radius of 10 km around the focal firm (FR_1), and an outer ring consisting of neighbors located within a radius of 25 km around the focal firm (FR_2). Considering that we can also write $FR_1 = FR_2 + \Delta$, Equation (C2) becomes:

$$KD \;=\; \beta_1 (FR_1 - FR_2) + \gamma' X + \eta, \tag{C3}$$

where $\eta \equiv [\delta Z + (\beta_1 + \beta_2) FR_2]$ is the error term. If Δ is uncorrelated with X and Z, Equation (C3) conservatively estimates the spatial spillover effect (i.e., β_1). In fact, FR_2 in the error term is certainly negatively correlated with $(FR_1 - FR_2)$, biasing a positive value of β_1 toward zero.

As argued by Grinblatt et al. (2008), if Δ is uncorrelated with the set of control variables, we can reasonably expect that this lack of correlation extends to those characteristics that we cannot observe. Table C1 shows that none of the control variables included in the analysis are notably correlated with the neighborhood difference variable.

Table C1. Pairwise correlation coefficients between $FR_1 - FR_2$ and X

	ROA	TA	LEV	IC	WC	SIZE	IND_R
$FR_1 - FR_2$	0.0000	0.0060	0.0026	-0.0046	-0.0031	0.0011	0.0058

Notes. This table reports the pairwise correlation coefficients between the set of control variables used in the analysis and the differential flood risk between a neighborhood of 10 and 25 km around the focal firm.

Table C2 reports the estimates of Equation (C3). Column (1) considers firms with DFR (10 km)<0, while Column (2) considers firms with DFR (10 km)>0. Both columns indicate, however, that having a closer neighborhood that is riskier than a more distant one results in higher borrowing costs. Consequently, Table C2 confirms the existence of local spatial effects as a result of risky neighbors.

Table C2. Cost of borrowings and nearest neighbors

	Column (1)	Column (2)
Constant	0.1754***	0.1802***
	[163.23]	[167.40]
$\overline{FR}_{N_i}(10km) - \overline{FR}_{N_i}(25km)$	0.0039***	0.0035***
	[3.21]	[3.08]
Firm's controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Mundlak's correction	Yes	Yes
Municipalities Fixed Effects	Yes	Yes
Observations	206,396	195,976
Sample	DFR (10 km)<0	DFR (10 km)>0
Adjusted R^2	0.353	0.356

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.*

As a further robustness test, we also performed a placebo regression design to exclude that, although formally located in municipality m_i, firm i may be sufficiently close to municipality m_j to share most of its characteristics (such as elevation, defenses, etc...). In this situation, FR_i might not accurately measure the firm's flood risk, and DFR could simply correct for measurement errors in FR.

If this is the case, our spatial effect should vanish once we account for the average distance between the firm and its neighbors. Indeed, firms that are located relatively far from their neighbors are less likely to share common local characteristics. Based on this reasoning and the fact that a 10-km radius allows us to account for a large area (more than 314 km^2) surrounding firm i, we conducted a placebo test by including the average distance to neighbors in our main regressions. Table C3 shows that our results continue to hold even when we control for neighbors' proximity to the focal firm.

Table C3. Cost of borrowings and km to neighbors

	Column (1)	Column (2)	Column (3)
Constant	0.1770***	0.1761***	0.1789***
	[197.49]	[133.95]	[131.56]
DFR (10 km)	0.0028***	0.0018	0.0041***
	[3.91]	[1.50]	[3.70]
Km to neighbors	0.0001	0.0000	-0.0000
	[1.60]	[0.31]	[-0.32]
Firm's controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Mundlak's correction	Yes	Yes	Yes
Municipalities Fixed Effects	Yes	Yes	Yes
Observations	402,372	206,396	195,976
Sample	DFR≠ 0	DFR (10 km)<0	DFR (10 km)>0
Adjusted R^2	0.354	0.352	0.356

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.*

D. ADDITIONAL ROBUSTNESS TESTS

Considering that some of the control variables may themselves be affected by flood risk and flood risk spillovers, we also perform our main analysis without controlling for firm-year-municipalities. As can be seen in Table D1, our conclusions are robust to this issue.

Table D1. Flood risk and cost of borrowings

	Column (1)	Column (2)	Column (3)
Constant	0.0582***	0.0583***	0.0581***
	[44.76]	[46.06]	[44.58]
FR	0.0024***	0.0039***	0.0040***
	[2.65]	[3.02]	[2.85]
DFR (10km)		0.0041***	0.0042***
		[2.88]	[2.74]
Firm's controls	NO	NO	NO
Year Fixed Effects	NO	NO	NO
Mundlak's correction	NO	NO	NO
Municipalities Fixed Effects	NO	NO	NO
Observations	419,040	419,040	402,372
Sample	Full	Full	DFR ≠ 0
Adjusted R^2	0.002	0.003	0.003

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed). t-statistics are presented in parentheses and are based on standard errors clustered at the NUTS3 level.*

As an additional robustness test, we repeated our analysis separately using the two flood risk indicators for persons and areas. Table D2 shows that spatial spillovers significantly impact the cost of debt, even when we consider our two risk indicators separately.

Table D2. Separate indicators of flood risk and cost of borrowings (Spatially lagged models)

	FR_{pop}	FR_{pop}	FR_{area}	FR_{area}
	Column (1)	Column (2)	Column (3)	Column (4)
Constant	0.1780***	0.1780***	0.1780***	0.1780***
	[239.48]	[239.39]	[239.50]	[239.38]
SIZE	-0.0121***	-0.0117***	-0.0121***	-0.0118***
	[-27.15]	[-25.72]	[-27.15]	[-25.66]
FR x SIZE		-0.0031***		-0.0021***
		[-5.80]		[-3.76]
DFR (10 km)	0.0141**	0.0684***	0.0276***	0.0649***
	[2.49]	[4.99]	[4.53]	[4.20]
DFR (10 km) x SIZE		-0.0037***		-0.0026***
		[-4.45]		[-2.68]
Firm's controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Mundlak's correction	Yes	Yes	Yes	Yes
Municipalities Fixed Effects	Yes	Yes	Yes	Yes
Observations	419,040	419,040	419,040	419,040
Sample	Full	Full	Full	Full
Adjusted R^2	0.354	0.354	0.354	0.354

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.*

In Table D3, we repeated our main regressions by dividing DFR into quartiles. Consistently with previous results, the spatial effect was particularly large and significant in the last quartile of *DFR* (i.e., for firms characterized by a DFR of at least 0.145).

Table D3. Cost of borrowings (Quartiles of *DFR*)

	Column (1)	Column (2)
Constant	0.1771***	0.1756***
	[212.63]	[105.71]
DFR (10 km) – 2° Quartile	0.0000	-0.0042**
	[0.08]	[-2.05]
DFR (10 km) – 3° Quartile	0.0011*	0.0049**
	[1.95]	[2.05]
DFR (10 km) – 4° Quartile	0.0023***	0.0114***
	[3.51]	[4.54]
DFR (10 km) – 2° Quartile x SIZE		0.0003**
		[2.15]
DFR (10 km) – 3° Quartile x SIZE		-0.0003*
		[-1.66]
DFR (10 km) – 4° Quartile x SIZE		-0.0006***
		[-3.81]
FR x SIZE		-0.0004***
		[-5.67]
SIZE	-0.0121***	-0.0120***
	[-27.15]	[-26.27]
Firm's controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Mundlak's correction	Yes	Yes
Municipality Fixed Effects	Yes	Yes
Observations	419,040	419,040
Adjusted *R*2	0.354	0.354

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.*

In table D4, we reproduce the main analysis as in Table (3) controlling also for natural disasters happened at municipality level during the period 2016-2019.

Table D4. Flood risk and cost of borrowings

	Column (1)	Column (2)	Column (3)
Constant	0.2387***	0.2338***	0.2339***
	[19.02]	[18.08]	[17.45]
FR	0.0009***	0.0014***	0.0015***
	[3.32]	[3.01]	[2.96]
DFR (10km)		0.0012**	0.0013**
		[2.06]	[2.07]
Natural Disaster	0.0044***	0.0041***	0.0042***
	[3.54]	[3.47]	[3.49]
Firm's controls	NO	NO	NO
Year Fixed Effects	NO	NO	NO
Mundlak's correction	NO	NO	NO
Municipalities Fixed Effects	NO	NO	NO
Observations	419,040	419,040	402,372
Sample	Full	Full	DFR ≠ 0
Adjusted R^2	0.002	0.003	0.003

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed). t-statistics are presented in parentheses and are based on standard errors clustered at the NUTS3 level.*

E. FLOOD RISK AND BANK COMPETITION

This section contains a mechanism analysis to support the hypothesis that the spatial effects we observed are a result of a bargaining process between firms and financial intermediaries. We proxied intermediaries' bargaining power with the number of local branches of firms operating in the financial sector (NACE 2-digit code 64) within the neighborhood of the focal firm. To normalize this measure to 1 and account for the relative diffusion of financial intermediaries in Italy, we took the ratio between this number and the number of financial intermediaries observed in the neighborhood with the highest concentration of financial institutions.

If the spatial effects of flood risk are due to the low bargaining power of Italian firms, particularly small ones, then these effects should be more pronounced in locations where there are few financial intermediaries. The lack of many competitors should, in fact, increase the monopolistic power of intermediaries.

Table E1 presents the pairwise correlation coefficients between the ratio of local branches operating in the financial sector and the three main measures of flood risk. These coefficients revealed a very small positive correlation between the ratio of local branches and firms' flood risk, as well as between the ratio of local branches and neighbors' flood risk.

Table E1. Pearson's correlation coefficients

	#	1	2	3	4
Local Branches	1	1			
FR	2	0.032***	1		
FR (10km)	3	0.042***	0.794***	1	
DFR (10 km)	4	0.001	-0.619***	-0.015***	1

*Notes. N. Obs. 419,040. *, ** and *** indicate statistical significance at the 0.1, 0.05 and 0.01 levels (two-tailed), respectively.*

Table E2 shows the estimates of Equation (2) in the article augmented by the ratio of local branches operating in the financial sector. Columns (1) and (2) present the results for firms surrounded by safer and riskier neighborhoods, respectively. Columns (3) and (4) repeat the analysis by further restricting the sample to firms with a SIZE below the median, while Columns (5) and (6) consider firms with a SIZE above the median. The results in Table E2 are consistent with our hypothesis that the positive coefficient of DFR (10 km) is primarily due to small firms located in areas with little competition among financial intermediaries.[4]

Table E2. Banks concentration, flood risk and cost of borrowings - (Spatially lagged models)

	Column (1)	Column (2)	Column (3)	Column (4)	Column (5)	Column (6)
Constant	0.1772***	0.1784***	0.2081***	0.2084***	0.1309***	0.1337***
	[131.60]	[153.06]	[61.76]	[63.91]	[56.76]	[63.77]
DFR (10 km)	0.0009	0.0052***	0.001	0.0063***	0.0013	0.0031*
	[0.74]	[4.34]	[0.51]	[3.53]	[0.85]	[1.79]
DFR (10 km) x Local Branches	0.0112***	-0.0119***	0.0115*	-0.0241***	0.0063	-0.0061
	[2.63]	[-2.76]	[1.91]	[-3.13]	[1.07]	[-1.17]
Local Branches	-0.0036	0.0012	-0.0105**	0.0140***	0.0012	-0.0058*
	[-1.37]	[0.43]	[-2.32]	[2.75]	[0.41]	[-1.66]
Firm's controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak's correction	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	206,372	195,960	102,714	97,563	103,605	98,353
Sample	DFR<0	DFR>0	DFR<0	DFR>0	DFR<0	DFR>0
Firms	All	All	Small	Small	Large	Large
Adjusted R^2	0.353	0.356	0.352	0.356	0.280	0.280

*Notes. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on robust standard errors.*

[4] We also extended the interaction analysis proposed in Table 4 of the article by allowing for other possible interaction effects between DFR and the observed firm's characteristics. We found that the only significant interaction effect, other than the one with SIZE, is the one with interest coverage. More precisely, firms with a higher interest coverage are less exposed to negative spatial effects. This finding is consistent with our idea of bargaining power. Indeed, a firm with a high-interest coverage is considered by banks as more secure, which increases its bargaining power. A t-test statistic confirmed that large firms (i.e., those analyzed in Columns 5 and 6 of Table E1) also exhibit a higher interest coverage.