Climate change and bank lending: the case of flood risk in Italy

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August 2019

Abstract

Do banks take into account the risk of climate-related natural catastrophes? We analyze bank lending to firms at risk of flooding using a new map of flood risk of Italy. We construct an indicator of long-term climate risk at municipal level as the share of firms located in high flood risk areas within each municipality and estimate the effect of climate risk on credit allocation. We find that the amount of loans granted to firms depends negatively on their climate risk exposure, independently of credit demand factors and of disaster insurance coverage. The results suggest that banks are aware of climate-related catastrophe risk and ration credit to risky firms.

JEL classification: G21, P48, Q54

Keywords: climate change, natural disasters, bank lending, credit rationing, flooding

*Bank of Italy, Directorate General for Economics, Statistics and Research. We are indebted to Andrea Orame for providing us with high quality loan data. We thank the ISPRA research team for useful clarifications on ISPRA data. We also thank many colleagues at the Bank of Italy and the participants in the 2019 annual conference of the European Economic Association, the 3rd Banking Research Network workshop and the 30th Villa Mondragone International Economic Seminar for their useful comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy. All the remaining errors are ours. E-mail: ivan.faiella@bancaditalia.it, filippo.natoli@bancaditalia.it.

1 Introduction

Climate change is causing a structural transformation of the natural environment. One important effect of this ongoing process is the increasing frequency and intensity of adverse natural events. In Italy, floods have been among the most destructive climate-related catastrophes, and flood damage has increased steadily in the last decade (Figure 1.1, left panel). Moreover, global warming is estimated to raise significantly the probability of large floods in the long run: according to Alfieri et al. (2015), their frequency will almost double by 2050 and triple by 2080, making Italy the country at highest risk of flood in Europe after the Netherlands (Figure 1.1, right panel).

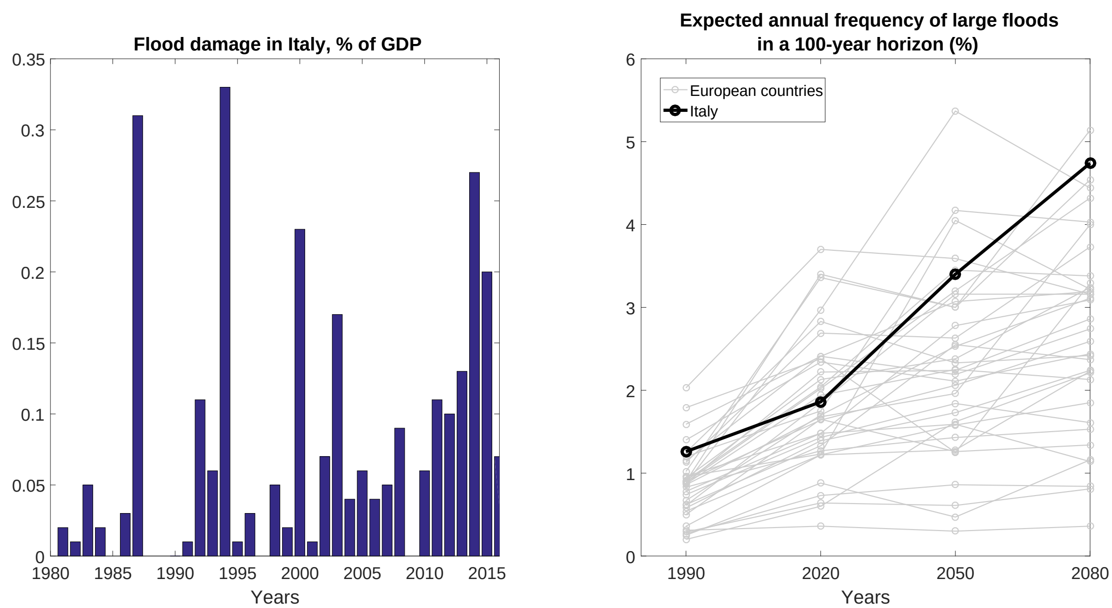

Figure 1.1: Left panel: Flood damage in Italy as a percentage of GDP. Data source: ISPRA. Right panel: expected annual frequency of large floods in a 100-year horizon by European country, in %. Black line: Italy; grey lines: the other 36 European countries in the sample. Data source: Alfieri et al. (2015).

Climate change poses material risks for the economy and for financial stability. Banks are naturally exposed to climate risks via their assets with longest maturity. One important question is whether banks are sensible to those risks and incorporate them in their credit allocation strategy. While the ex-post effects of natural catastrophes on bank business have been extensively investigated, there is lack of papers analyzing the banks' *ex-ante* perception of and attitude towards the long-run risks induced by climate change. We aim at filling this gap by studying the connection between climate risk and bank lending using data on credit to Italian firms located in areas at risk of flood. To implement the Flood Directive of the European Commission, in 2015 the Italian Institute for Environmental Protection and Research (ISPRA) constructed a map of flood risk of Italy at the highly granular municipal level.[1] Land is classified in four flood risk categories (no risk, low, medium and high risk): lands at high risk are estimated to be damaged once in 20–50 years while, those at lower risk, only once in more than 200 years. We use this mapping to estimate the effect of long-term climate risk on the lending behavior of banks. We construct an indicator of firms at risk as the share of firms located in high-risk flood areas within each municipality and, as flood frequency in those areas is high enough to affect bank business, use it as an indicator of the climate risk faced by banks when lending to firms.

The analysis is conducted in two steps: first, we match data on flood risk with micro data on bank loans to firms from the Italian Central Credit Register, where the latter have been previously aggregated at municipal level according to the final use destination of credit; second, we test whether the level of flood risk affects the amount of credit granted to firms. In order to investigate the drivers of the credit-risk relationship we include, on top of province- and industry-level fixed effects, some key control variables: (1) the municipal value added, to control for the endogeneity between firms' performance and risk exposure; (2) a dummy for flooded municipalities in 2014 (the year with largest flood damages in the last decade) identified as those with flood-related tax exemption by the Ministry of Finance, to control for demand and supply motives due to recent catastrophes; (3) an indicator of catastrophe insurance penetration at province level, based on specific questions included in the Bank of Italy's Survey of Industrial and Service Firms for year 2016. The baseline estimates are carried out with 2014 credit data; estimates are also repeated with credit data from 2010 to 2016, to assess whether banks' attitude has changed in times of rising public attention on climate change.

Two results stand out. First, climate risk has a negative impact on bank lending, i.e. lower credit is allocated in municipalities at higher risk. The climate risk variable is always significant at 1% level, and has a good explanatory power for bank credit in terms of R squared. Results are robust when controlling for all of the above mentioned variables. Second, the relationship between climate risk and bank lending appears to have been relatively stable between 2010 and 2016, suggesting no particular variation of banks' allocation strategies over time. As a robustness test, we repeat our regressions using data aggregated from a different proprietary dataset, which is based on the surveillance reports compiled by private banks for the Bank of Italy. This alternative data source, while being at province instead of municipal level, makes it possible to control for a wider set of

[1] Municipalities in Italy have a median land surface of only about 20 km^2.

factors, like bank and firm size. Results from the robustness analysis confirm our previous findings for the subset of loans granted to small and medium-sized enterprises. All in all, our results suggest a supply-side story: banks are aware of long-term, climate-related catastrophe risk and do discriminate borrowers by granting less credit to risky firms.[2] Our control variables, which account for a a wide set of potential demand drivers such as lower credit to less profitable, damaged firms or to more exposed sectors, leave no other apparent reasons for a firm for getting less credit if located in more risky areas.

This paper contributes to different strands of the literature. First, it contributes to the recently growing literature on the economic effects of climate change. Banks appear to be aware of climate-related risks, in line with de Greiff, Delis, and Ongena (2018), who find that banks have priced climate policy risk since 2015, and Krueger, Sautner, and Starks (2018), who survey institutional investors who recognize climate-related risk as an important source of risk to be managed. Our paper is complementary to them being the first, as far as we know, which explores the actual behavior of banks towards this risk, looking at the physical (not policy) risk induced by climate change. We do this by adopting a micro data perspective, using a unique dataset obtained by merging different proprietary sources. Second, it also contributes to the empirical literature on natural catastrophes. With respect to most of this literature, which is based on the ex-post effects of extreme events, we draw our results from an ex-ante evaluation of risk, and show that those results hold independently of the occurrence of the catastrophe itself; moreover, the analysis is carried out on the universe of bank-firm credit relationships, not only on credit granted in specific areas, so it cannot be biased by sample selection. Third, it contributes to the literature on credit rationing by identifying an additional driver of rationing on the side of the lender, who makes a "climate-risk screening" when granting loans to the business sectors.

The rest of the paper is organized as follows. Section 2 presents hydrogeological risk and describes the dataset. Section 3 explains the estimation strategy and comments on the obtained results. Section 4 proposes a robustness analysis with different credit data. Section 5 concludes.

Related Literature — The literature exploring the connection between banking activity and climate change is growing fast, but it is still scant. Krueger, Sautner, and Starks (2018)

[2]We provide evidence of credit rationing, but discrimination may also imply higher credit costs or stricter credit guarantees. While data on loan prices exist from a different data source, they are incomplete and fragmented, so we prefer not to include them in the analysis to not bias our credit-risk dataset. The analysis of these other variables is left for future research.

surveyed institutional investors regarding climate risk perception; the survey responses suggest that investors do consider the risks stemming from climate change, and prefer adopting a risk management or engagement strategy instead of divesting their funds. Battiston, Mandel, Monasterolo, Schütze, and Visentin (2017) use network analysis to measure the exposure of the financial sector in the Euro Area to climate risk, finding that while the direct exposure to fossil fuel companies is relatively small, it is however substantially amplified by the indirect exposure via financial counterparties. With respect to these papers, our work analyzes how banks deal with climate risk and, by means of a detailed mapping, is able to identify the amount of credit that is actually located in risky areas. The literature on climate policy risk is a bit larger than that on physical climate risk. Concerning the policy risk for banks, de Greiff, Delis, and Ongena (2018) evaluate the extent to which risk is priced in syndicated loans to firms: using data on global fossil fuel reserves they find that, since 2015, the cost of credit has become substantially higher for fossil fuel vs. non-fossil fuel firms; Huang et al. (2019) study the impact of the Clear Air Action policy enacted by the Chinese government in 2013 on credit granted to the business sector, finding an increase in the rate of default and credit cost for highly-polluting firms. On climate risk borne by firms, Ilhan, Sautner, and Vilkov (2019) investigate the effect of carbon emissions on the risk of sharp market devaluations of S&P 500 firms, finding that risk is concentrated in high-emission industries and rises in times of high policy attention; Ginglinger and Moreau (2019) evaluate whether climate risk affects the capital structure of firms: using climate scenarios, they find that firms at higher risk are less leveraged than less exposed firms.

Another strand of the literature investigates the effects of natural catastrophes, without explicit links to climate change. Some of them focus on local socio-economic effects, such as the direct economic and demographic damage (Cavallo et al., 2010) and the variation in growth rates in affected cities (Strobl, 2011), as well as on the risks and opportunities linked to reconstruction (Vigdor, 2008). Others look at macroeconomic implications in terms of short- and long-term growth (Cavallo et al., 2013; McDermott et al., 2014), of cross-country capital flows (Odell and Weidenmier, 2004) and of the different effects in advanced versus emerging economies (Noy, 2009). The reported results, while rich in terms of economic analysis, mainly come from the evidence on hurricanes and earthquakes, so they are not representative of the entire spectrum of hydrogeological events. Moreover, they mostly focus on the United States, and in particular on specific areas of that country that have historically suffered the most from those types of natural catastrophe.

From a theoretical point of view, natural catastrophes have been analyzed in the same frameworks that embed large macroeconomic shocks, or rare disasters. Starting from the seminal work of Rietz (1988), the literature on rare disasters has emphasized the effects of a non-negligible probability of disasters on equilibrium asset prices (Barro, 2006; Barro and Ursúa, 2012; Gabaix, 2012; Gourio, 2012; Wachter, 2013). While theoretical models typically do not include the banking sector, an empirical strand of the economic literature investigates the link between natural disasters and bank lending. Morse (2011) analyzes the role of payday lenders in mitigating financial distress caused by natural disasters; Cortés and Strahan (2017) investigate how banks alter their credit supply decisions in response to shocks to local credit demand provoked by natural disasters; Garmaise and Moskowitz (2009) analyze the implications of earthquake risk on real estate financing. A literature review on the consequences of natural disasters on banks is reported in Klomp (2014).

Few papers before ours have specifically focused on floods. Looking at a number of flood events in the UK and to housing market developments in affected areas, Lamond et al. (2010) do not find broad-based evidence of a strong and persistent impact of floods on house prices; opposite evidence is instead reported in Belanger and Bourdeau-Brien (2017) who examine the effects of flood risk on property prices in the United Kingdom and find a significant "flood risk discount" for both waterfront properties and real estate that is located farther away within the same area. Koetter et al. (2016) exploit the 2013 Elbe flooding in Germany to assess how lending behaviour changed after that event, finding that local banks with sound relationships with flooded firms lent more than large banks in the aftermath of the flood, mitigating the effects of the shocks on the industry sector. With respect to all the empirical literature on natural disasters, we adopt a unique ex-ante perspective, so we do not need to identify natural catastrophes as shocks and study credit dynamics in affected and unaffected areas.

2 Data description

In this Section we present evidence on flood risk in Italy, looking at the geographical distribution of local business units in high risk areas across the country. Then, we construct an indicator of climate risk at municipal level and explore the relationship between bank loans and flood risk.

2.1 Flood risk and the business sector

Italy is heavily exposed to hydrogeological risk (mainly related to floods and landslides) because of its geomorphological characteristics and the intense urbanization that followed the post-war economic boom. Floods have historically been less frequent than landslides, but the number of casualties and damages associated with flood events has been higher than that of landslides, at least in the last decades (Faiella, 2013). Flood damage, in % of GDP, has been highest in 1987, 1994 and 2014, and is trending upwards since the early 2000s (Figure 1.1, left panel); moreover, the frequency of floods is projected to increase significantly: climate simulations made with a hydrogeological model show that flood frequency in Italy could almost double by 2050 and triple by 2080 (Alfieri et al., 2015) (Figure 1.1, right panel).

In order to support national climate-related policies, Trigila et al. (2015) have created a database of the population (households, firms and cultural heritage sites) exposed to the risk of flood and landslide throughout Italy (the ISPRA report, henceforth). The database has been constructed in two steps: first, for each of the two types of natural event, land has been categorized in terms of riskiness using granular environmental data and information about the historical occurrence of each event; second, both land datasets have been matched with data on the geographical residence of households, firms and cultural heritage sites taken from the 2011 ISTAT census (the last one available), obtaining statistics of the population exposed to flood and landslide risk at different risk levels.[3]

For all of the above reasons, provided that a joint flood-landslide risk mapping is unavailable, we restrict our analysis to flood risk. Land categorization for flood risk is constructed using data collected from river basin authorities, municipalities, provinces, regions and other public authorities.[4] A large set of data is then used to calibrate hydraulic and hydrological models which produce forecasts of the flow of the rivers and of rainfall amounts; in turn, these forecasts are used to estimate the frequency of flood events over time. According to these estimates, land is categorized as at low, medium, high or at no risk of flood: areas in which floods are estimated to occur once in 20-50 years are flagged as high-risk areas, while those in which floods are estimated to be less frequent (once in 100-200 years and once in more than 200 years) are labelled as medium-

[3]For further details on the ISTAT census, search *IX Censimento generale dell'industria e dei servizi e Censimento delle istituzioni non profit* at `www.istat.it`. ISTAT censuses of firms have been traditionally conducted once every ten years. The first permanent census will take place in 2019.

[4]River basin authorities are public entities in charge of supervising the conservation and sustainable use of river resources, pursuing hydrogeological risk mitigation policies and contributing to the programming of structural and non-structural measures.

and low-risk areas, respectively. Areas at lower risk are farther from the river basins and damaged only in the case of large floods: indeed, in the classification made in the ISPRA report, low-risk areas include medium-risk ones, and medium-risk areas include high-risk ones. Figure 2.1 shows the geographical distribution over Italy of areas at low-risk (left picture), medium-risk (center picture) and high-risk (right picture), with grey lines indicating regional borders. According to the maps, in 2014 10.6 percent of the territory of Italy was exposed to flood risk, of which 4.0 percent to high risk.

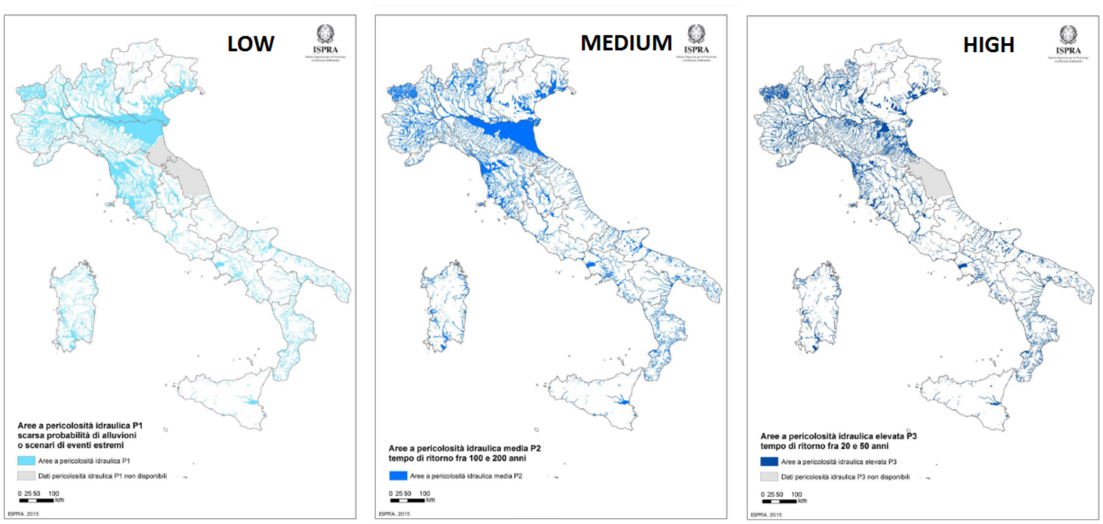

Figure 2.1: Categorization of Italy in terms on flood risk. Left picture: low-risk areas (light blue); center picture: medium-risk areas (blue); right picture: high-risk areas (dark blue). Grey lines indicate regional borders. Source: Trigila et al. (2015)

In this paper we focus on the flood risk of Italian firms, leaving households and cultural heritage sites for future research. Concerning firms, the ISTAT census reports details of the Local Business Units (LBUs henceforth), defined as "economic units that perform arts and professions in industry, trade and services in favor of enterprises and households". In general, firms' activity is organized in more than one LBU: in the census, ISTAT assigns the exact geographical location to each of them, irrespectively of the legal residence of the company. This aspect is key in our investigation because it allows for a correct quantification of the physical risk concentrated in each municipality. Table 1 shows the geographical distribution of LBUs at risk of flood by the 20 Italian regions: 18.3 percent of the total LBUs are exposed to flood risk, of which 3.9 per cent are at high risk. Looking at the regional breakdown, Emilia-Romagna, Veneto, Liguria, Tuscany and Sardinia have the highest concentration of LBUs at high-risk: these regions together produce

	# LBUs	LBUs at risk by risk level			share by risk level (%)			Value Added
		high	medium	low	high	medium	low	(% of tot VA)
Abruzzo	109,925	2,135	13,435	3,569	1.9	12.2	3.2	1.9
Basilicata	38,043	219	333	352	0.6	0.9	0.9	0.6
Calabria	117,904	3,924	4,900	6,749	3.3	4.2	5.7	1.9
Campania	362,502	6,010	15,098	17,788	1.7	4.2	4.9	6.2
Emilia Romagna	403,272	40,665	254,337	160,280	10.1	63.1	39.7	9.0
Friuli	95,940	2,573	7,505	9,817	2.7	7.8	10.2	2.2
Lazio	456,377	7,060	13,134	54,156	1.5	2.9	11.9	11.4
Liguria	140,737	25,114	37,376	47,570	17.8	26.6	33.8	2.9
Lombardy	888,054	18,867	28,578	97,879	2.1	3.2	11.0	22.1
Marche	142,657	836	7,101	3,629	0.6	5.0	2.5	2.5
Molise	23,254	126	444	541	0.5	1.9	2.3	0.4
Piedmont	369,062	7,835	18,843	58,112	2.1	5.1	15.7	7.6
Puglia	269,834	4,927	7,926	10,186	1.8	2.9	3.8	4.3
Sardinia	117,588	4,931	7,817	19,431	4.2	6.6	16.5	1.9
Sicilia	291,506	1,014	1,609	1,874	0.3	0.6	0.6	5.3
Tuscany	358,984	23,281	105,605	257,770	6.5	29.4	71.8	6.8
Trentino	91,614	1,600	2,224	5,136	1.7	2.4	5.6	2.3
Umbria	75,262	2,682	5,750	9,187	3.6	7.6	12.2	1.3
Valle D'Aosta	12,876	573	1,245	5,209	4.5	9.7	40.5	0.3
Veneto	440,623	31,894	43,275	110,129	7.2	9.8	25.0	9.2
Total	**4,806,014**	**186,266**	**576,535**	**879,364**	**3.9**	**12.0**	**18.3**	100

Table 1: Statistics on flood risk by Italian region. Column 1: total number of LBUs from the 2011 Census; columns 2 to 7: number of LBUs at risk and percentages by risk level (from the ISPRA report); column 8: regional share of national value added, computed from ISTAT data. Data on LBUs at risk for Marche are an underestimate of the number of firms at risk in that region.

almost a third of the national value added.[5]

In order to investigate the exposure of the banking sector to flood risk, we only consider the fraction of LBUs at high risk (i.e. those located in dark blue areas of Figure 2.1). The reason for this choice is that the investment horizon of banks is limited: in medium- and low-risk areas, flood damage can be so infrequent that banks are unlikely to consider it, while floods occurring once in 20 to 50 years (i.e., in high-risk areas) are sufficiently frequent to be considered by banks when financing firms' activity.

2.2 Climate risk indicator

As Figure 2.1 clearly shows, flood risk is not only spread unequally among regions and provinces, but also *within* each province. The ISPRA dataset is available at municipal level, so we take the municipality as reference unit in our analysis.[6] We define our indi-

[5]Statistics on landslide risk in the ISPRA report show, instead, that only 1.7 percent of LBUs is at high or very high risk, with most of them located in only one region (Valle d'Aosta) producing the 0.3 percent of national value added. For this reason, in the rest of the paper we focus only on flood risk, the most significant hydrogeological risk for investment financing in Italy.

[6]At the time of constructing this dataset, municipal data for high flood risk areas, which are not present in the ISPRA report, were available on the *Italia Sicura* website.

cator of climate risk per municipality j as the share of LBUs at high risk of flood over the total number of LBUs located in municipality j:

$$\textbf{ClimRisk}_j = \frac{\text{LBUs at risk }_j}{\text{total number of LBUs }_j} \tag{2.1}$$

In order to give a synthetic description of the flood risk by municipality, we divide municipalities into two groups: Low-Impact Flooding (LIF), which encompasses municipalities with a share of exposed LBUs lower than the 75th percentile (around 3 percent), and High-Impact Flooding (HIF), with an equal or higher share of exposed LBUs.[7] Table 2 reports the number of LIF and HIF municipalities for each region. HIF municipalities are mostly concentrated in Piedmont, Lombardy and Emilia Romagna.

Region	**LIF**	**HIF**	**Total**
Abruzzo	290	15	305
Basilicata	128	3	131
Calabria	287	122	409
Campania	475	76	551
Emilia-Romagna	174	174	348
Friuli-Venezia Giulia	187	31	218
Lazio	340	38	378
Liguria	98	137	235
Lombardy	1228	316	1544
Marche	24	9	33
Molise	134	2	136
Piedmont	855	351	1206
Puglia	212	46	258
Sardinia	310	67	377
Sicilia	378	12	390
Tuscany	155	132	287
Trentino	315	18	333
Umbria	65	26	91
Valle d'Aosta	24	50	74
Veneto	481	100	581
All	6160	1725	7885

Table 2: Municipal-level distribution for class of Flooding Impact in 2014. The High-Impact Flooding (HIF) class contains municipalities with a share of exposed LBUs greater than 3 percent; Low-Impact Flooding (LIF) municipalities are the remaining ones. Data on the remaining 170 municipalities are missing.

[7] The 75th percentile is arbitrarily chosen for illustrative purposes. This choice does not affect results in the regression analysis, which is carried out using the ClimRisk indicator of Equation 2.1.

2.3 Bank loans to risky firms

If floods damage LBUs, firms can suffer business disruptions and fail to pay back their debt obligations. Therefore, financial intermediaries are exposed to natural catastrophes through their loans, other than through their own offices located in risky areas. This indirect channel should be substantial in Italy, given that Italian firms mainly rely on the banking system to raise external finance. Indeed, for Italian non-financial companies bank debt represents about 70 percent of total debt, compared with 38 percent in France, 49 in Germany, and 30 percent in the UK (Accetturo et al., 2013).

We investigate the indirect exposure of banks using loan data. Credit granted by banks operating throughout Italy is available from the Italian Central Credit register. We consider the entire universe of loans (including those classified as non-performing) granted to the non-financial business sector which is legally resident in Italy, excluding producer families, the agricultural sector and uncategorized firms. In order to match the granularity of the climate risk indicator, we aggregate loan data at municipal level, obtaining the total amount of outstanding credit in each municipality for each industry sector.[8] It is important to note that the aggregation is not made by the legal residence of the borrower but by the municipality of the bank branch who granted credit: indeed, given that firms may operate in different areas (possibly more risky) than those in which they are legally resident, this methodology seems to better proxy the final use destination of credit, which matters when classifying credits at risk of floods. The aforementioned selection and aggregation procedure has been applied to the annual stock of loans in different periods, i.e. between 2010 and 2016, ending up with seven years of aggregated credit data. In 2014, year in which the land classification was released, the stock of outstanding loans was 1.9 trillion euros, of which 794 billion granted to our non-financial business sector; the matching by municipality is quite efficient, yielding a total amount of credit matched of 775 billions.

Table 3 displays the value of outstanding credit as of end-2014 , divided by LIF and HIF municipalities. More than 20 percent of total loans is granted in HIF municipalities, with the bulk of business loans at risk located in Lombardy, Veneto, Emilia Romagna and Tuscany. This evidence completes the overall picture, suggesting that climate-related catastrophe risk in Italy is material: as for LBUs, also the stock of credit at risk is located in municipalities of high-value added regions. Table 4 reports business loans, granted

[8]Obviously, the aggregation process eliminates loan-level information such as credit duration and loan issue dates, which are needed to construct credit flows aggregates. Our analysis, which focuses on the cross-sectional heterogeneity more than the time evolution of credit, is only based on credit stocks.

Region	LIF	HIF	Total
Abruzzo	9,763	1,037	10,801
Basilicata	2,040	18	2,059
Calabria	2,531	1,785	4,316
Campania	25,030	1,733	26,763
Emilia-Romagna	52,734	26,091	78,825
Friuli-Venezia Giulia	11,057	2,649	13,706
Lazio	64,498	2,006	66,504
Liguria	223	15,611	15,834
Lombardy	227,927	39,873	267,800
Marche	1,997	1,533	3,529
Molise	1,191	1	1,193
Piedmont	48,561	6,481	55,042
Puglia	15,261	2,950	18,211
Sardinia	4,927	2,814	7,740
Sicilia	18,366	37	18,404
Tuscany	49,059	22,860	71,919
Trentino	20,161	1,847	22,008
Umbria	6,105	2,933	9,038
Valle d'Aosta	580	262	842
Veneto	51,587	29,435	81,023
All	613,601	161,956	775,557

Table 3: Bank loans to firms for class of flooding impact and region: 2014 (mln euros).

in LIF and HIF municipalities, by borrower sector.[9] About 60 percent of loans in HIF municipalities is concentrated in four industries: construction, wholesale and retail trade, real estate activities and basic metals and plastic products.

3 Empirical analysis

In this Section we investigate the effect of climate risk on banking activity. In particular, we employ our environment-firm-credit dataset to estimate the elasticity of the credit stock to the variation in flood risk at municipal level. We also exploit the time dimension of our credit stock to test the risk-credit relationship in different years.

3.1 Regression setup

As a baseline exercise, we propose a set of regressions based on the simplest linear regression framework:

[9]The sectoral breakdown is based on ATECO sectors, i.e. the adaptation of Eurostat's NACE sector classification to the Italian industry by ISTAT.

#	Industry sector	LIF	HIF	Total
1	Mining	1,294	454	1,748
2	Food Products	22,462	6,105	28,567
3	Textiles	14,471	5,787	20,258
4	Wood and Products of Wood	9,229	2,694	11,923
5	Paper and Paper Products	6,874	2,134	9,009
6	Chemicals and Pharmaceuticals	12,173	2,592	14,764
7	Rubber and Plastic Products	7,932	2,025	9,956
8	Basic Metals and Metal Products	38,001	13,272	51,273
9	Electrical Equipment	8,751	2,174	10,924
10	Machinery and Equipment	16,490	4,787	21,276
11	Transport Equipment	7,795	1,718	9,512
12	Other Manufacturing	6,612	1,830	8,442
13	Electricity and Gas	33,882	5,608	39,490
14	Construction	106,765	30,639	137,404
15	Wholesale and Retail Trade	101,226	27,430	128,656
16	Transportation and Storage	34,246	5,903	40,149
17	Accommodation and Food Service	22,113	8,149	30,262
18	Information and Communication	13,031	1,556	14,587
19	Real Estate Activities	91,854	24,646	116,499
20	Professional Activities	25,929	5,596	31,525
21	Rental and Leasing Activities, Travel Etc	16,697	3,063	19,760
22	Other Service Activities	15,776	3,795	19,571
	All	613,601	161,956	775,557

Table 4: Bank loans to firms for class of flooding impact and industry: 2014 (mln euros).

$$\log(\text{loans})_{y,h,v,j} = \beta_0 + \beta_1 \log(\text{ClimRisk})_{v,j} + \delta \,\textbf{controls}\,_{y,h,v,j} + \epsilon_{y,h,v,j} \qquad (3.1)$$

where $\{y = 2010, \dots 2016\}$ indicates the reference year for the credit stock, $\{h = 1, \dots, 22\}$ the borrower's industry sector, $\{v = 1, \dots, 108\}$and $\{j = 1, \dots 7885\}$ the province and municipality in which credit is granted. Controls include key variables capturing demand and supply drivers of bank lending other than climate risk exposure, and regressions are carried out by adding them one at a time.

3.2 Results

Results of our baseline exercise, which encompasses six regression specifications, are displayed in Figure 5. For each regression we compute robust standard errors clustered at province level.

	(1) loans2014	(2) loans2014	(3) loans2015	(4) loans2016	(5) loans2016	(6) loans2016
ClimRisk	-0.174^{***}	-0.164^{***}	-0.159^{***}	-0.164^{***}	-0.109^{***}	-0.109^{***}
VAmunic2013		0.040^{***}				
VAmunic2014			0.039^{***}			
VAmunic2015				0.039^{***}	0.031^{***}	0.031^{***}
floods2014			0.5167	0.5797^{*}	0.3016	0.3016
lowinsured2016						-0.2468^{***}
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Observations	121,858	121,858	120,978	119,724	64,795	64,795
R^2	0.131	0.184	0.189	0.196	0.188	0.188

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Baseline exercise. Standard errors are clustered at province level (108 clusters).

Simplest specification. Specification (1) in Table 5 is the simplest one: the stock of loans in 2014 is regressed on the climate risk indicator, with no additional controls other than province-level fixed effects. Results show that our indicator is significant at 1% level and its coefficient has negative sign: a one-percentage point higher ClimRisk in municipality j entails a lower credit stock by 0.17 percentage points. The regression has an R-squared of 13%. With few exceptions, province-level dummies are significant at the one percent level (not reported in the table), indicating a strong relationship between lending activity and the geographical destination of loans.

Value added. Specification (2) augments Specification (1) by one of the most important control variable: the value added. On one hand, a high-value added municipality is composed by productive firms, which may demand more credit to expand their business; on the other hand, banks are more willing to give credit to borrowers with sound returns. With respect to Specification (1), value added might also be a key omitted variable because climate risk can be endogenous to it for different reasons: for example, low value-added firms may locate their plants in the cheapest areas (that can also be the most exposed to floods) within the municipality, so less credit to riskier municipalities may reflect less credit to low value added firms. Provided that data on municipal-level value added are not available for the universe of Italian municipalities, we take province-level measures from the ISTAT database and assign them to the municipalities within each province with the following two-step procedure: (1) we obtain per capita province-level value added by dividing total value added by the number of LBUs in each province, and (2) we re-weight the obtained values for the number of LBUs in each municipality.

Municipal-level value added is included in Specification (2) with one-year lag (i.e., 2013 value added against 2014 loans). Including this variable increases the share of explained variation of the stock of credit to 18%. The coefficient of value added is significant at the 1% level and has the expected positive sign; however, the ClimRisk variable remains highly significant.[10]

Flooded municipalities. The ClimRisk variable refers to a long-term risk of large floods. However, one may think that what matters in terms of flood-driven credit demand and supply is the actual occurrence of flood events. Indeed, on one side flooded municipalities may demand more credit to reconstruct the damage business units, or less credit in the short term to re-organize business or because of the intervention of public authorities. On the supply side, large floods may induce banks to make a tighter screening of loan applications by firms located in affected areas, and this behavior can be mistakenly confounded with a screening based on an ex-ante long-term risk assessment. In order to control for all factors linked to past flood events, we construct one dummy that is equal to one if the municipality has been hit by the flood, and zero otherwise.

Our dummy is based on the events occurred in 2014, year in which a number of large floods hit Italy and flood damage has been highest in the last 15 years. To help households and firms in damaged municipalities, in October of the same year the Italian Ministry of Economy and Finance enacted a decree (integrated by a press release issued two months later) to give tax exemption to all munciipalities hit by floods for fiscal year 2014.[11] Table 6 reports the total number of municipalities hit by flood by region and province, totalling about 3 percent of all municipalities.

The flood dummy is included as a control in our regression framework. While floods occurred mostly in autumn, the effects on credit, if any, can hardly appear in the same year's stock. For this reason, Specification (3) repeats Specification (2) with variables indexed one year forward (i.e., credit in 2015 and value added in 2014) and includes the 2014 flood dummy as an additional regressor; concerning the latter, its coefficient is positive but not significant. Provided that the effects of floods on credit may be even more

[10] Results do not change if contemporaneous value added is instead introduced.

[11] Decree No. 246 (22 October 2014) and press release No. 272 (1 December 2014) of the Italian Ministry of Economy and Finance.

Municipalities hit by floods in 2014		
Region	Province	Total number of flooded municipalities
Emilia Romagna	Parma, Piacenza	20
Friuli Venezia Giulia	Trieste	2
Liguria	Genova	67
Piedmont	Alessandria, Verbania	39
Tuscany	Grosseto, Livorno, Massa Carrara, Pisa, Pistoia	39
Veneto	Belluno, Padova, Rovigo, Venezia, Verona	50
6 regions	**16 provinces**	**217 municipalities**

Table 6: List of municipalities hit by flood in 2014 according to decree No. 246 (22 October 2014) and press release No. 272 (1 December 2014) enacted by the Italian Ministry of Economy and Finance.

lagged (i.e., credit to restart business may be asked and granted several months after the flood event), the same regression is repeated for the stock of credit in 2016, i.e. for credit outstanding about one year and half from the big floods. This time, the flood dummy is mildly significant with positive sign, suggesting that, if any, some additional demand due to reconstruction is relevant. However, the coefficient and significance of ClimRisk remain mostly unchanged.

Sectoral fixed effects. So far we have not controlled for the industry sector of the borrower in our regressions. However, there can be uncontrolled endogeneity between demand and supply factors related to the borrower's sector and climate risk: indeed, in some sectors, industrial sheds are more frequently located close to rivers (for operational or logistic needs) than in others, so the former are naturally more exposed to climate-related catastrophes than other sectors. Without sectoral controls, ClimRisk could therefore capture sectoral-specific demand and supply drivers of bank credit. Adding industry fixed effects to the previous set of regressors (Specification (5)) reduces the coefficient of ClimRisk that remains, however, highly significant.

Insurance coverage. In the previous regressions we did not control for the possibility that firms can be insured against flooding because data on flood insurance, as well as data on general catastrophe insurance coverage, have never been collected for the universe of the Italian business sector. In our analysis, the insurance coverage of firms against natural catastrophes may be a significant omitted variable, leading to an underestimate of the negative relationship between credit and climate risk. Indeed, if a loan applicant

Geographical area	Industry	Services	Total
North-west	8.4%	5.2%	6.9%
North-east	3.8%	2.5%	3.2%
Center	6.7%	5.8%	6.2%
South	5.9%	3.5%	4.4%
Total	6.3%	4.3%	5.3%

Table 7: Percentage of the companies interviewed that suffered losses or spent money to restore their business because of floods or landslides between 2012 and 2016, by geographical region of Italy and by sector (Question 1).

will use credit in areas at high risk but is insured against flood occurrences, the bank may choose to ignore its risk exposure knowing that any physical damage is reimbursed by the insurance company: provided that the percentage of insured firms might be higher in risky areas, this could entail a positive bias in the coefficient of ClimRisk.

To gain insights on this topic, we added two specific questions in the Industrial and Service Firms and the Business Outlook Survey on 2016, a business sector survey conducted annually by the Bank of Italy (`https://www.bancaditalia.it/pubblicazioni/indagine-imprese`). In particular, we asked the following two questions:

- Question 1: *Has your company suffered losses or spent money to restore its business because of floods or landslides during the last five years?* (Possible answers are: Yes; No; I dont' know/I don't want to answer)
- Question 2: *Are your business units and machinery insured against floods or landslides?* (Possible answers are: No, but we will do it; No, and we will not do it; Yes)

Results are reported in Table 7 and 8, where missing answers are imputed using standard statistical procedures. Of the whole set of interviewees, 5.3 percent had been affected by a hydrogeological event between 2012 and 2016, with the majority of them in the industrial sector and located in the north-west and in the center of Italy; 44 percent of interviewees are insured against damage caused by floods or landslides, with the lowest insurance coverage in the south of Italy.[12]

While this percentage is only related to the sample of large firms (with 20 or more employees) which are targeted by the Survey, it is not, by itself, negligible. For this reason, we aggregate all the obtained responses at province level and use them to con-

[12] More details on the results are available upon request.

Geographical area	Industry	Services	Total
North-west	50.4%	41.4%	46.9%
North-east	51.0%	42.6%	47.3%
Center	44.1%	44.1%	44.1%
South	39.2%	28.7%	32.7%
Total	48.0%	39.6%	43.7%

Table 8: Percentage of the interviewed companies which was insured against floods or landslides as of 2016, by geographic region of Italy and by sector (Question 2).

struct a proxy of the flood insurance coverage in our framework.[13] In particular, we order all provinces based on the percentage of insured firms within each province and construct a dummy equal to 1 if a province has low insurance penetration (i.e., a percentage of insured firms within the province that is below the 25th percentile), and zero otherwise. Specification (6) augments Specification (5) with the low-insurance dummy, which is highly significant with the expected negative sign (low insured firms receive less credit). Again, the magnitude and significance of ClimRisk remains unchanged.

3.3 Time dimension

As the stock of credit is available for seven years in a row, it is worth to analyze the impact of ClimRisk on credit in different time periods to give insights on the evolution of bank attitude towards risk. On one side, one might expect that the perception of risk of natural catastrophes induced by climate change has increased, given the heightened attention on climate change issues in the current decade: indeed, media coverage of this topic by Italian newspapers has more than tripled since 2010 (see Figure 3.1). Moreover, the ISPRA flood risk mapping, released in 2015, is the fist complete mapping of flood risk in Italy, and banks could have taken this new source of information into account in their lending strategy since then. On the other side, the high presence of small local banks in the Italian banking sector, with tight relationships with borrowers, may suggest that banks have always been aware of these catastrophe risks (which pertain to the territory in which they operate) and that, for this reason, their attitude towards them cannot be radically altered by the ongoing policy debate.

The analysis targets credit stocks in different years, which are regressed on the ClimRisk

[13]The aggregation is made at province and not at municipal level because the municipality identifier in our dataset does not match with that in the survey.

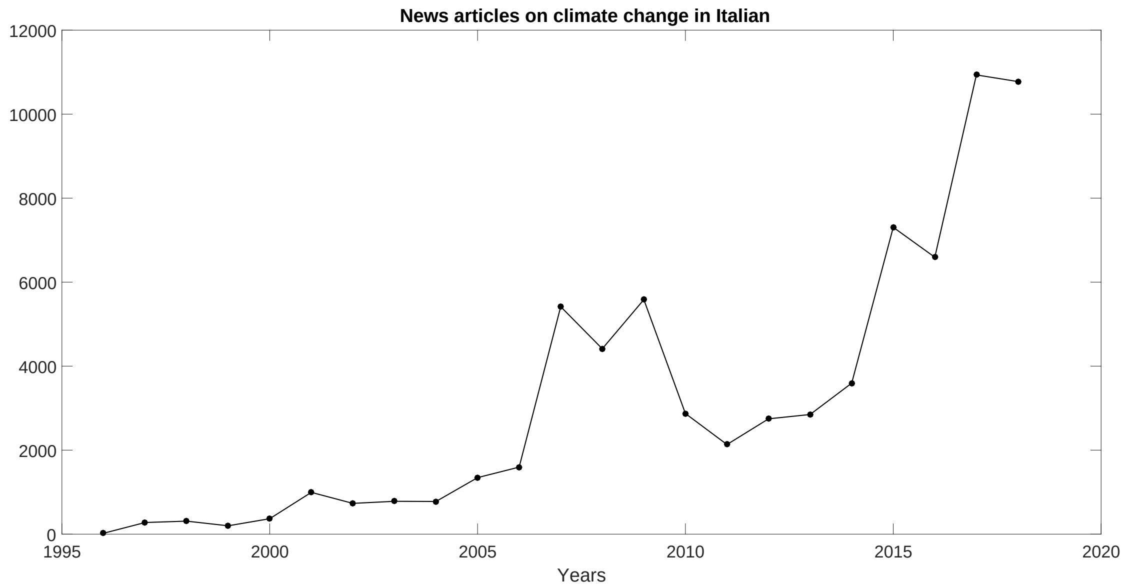

Figure 3.1: Number of newspaper articles in Italian containing words related to climate change, made with the FACTIVA news search tool. The words included are "cambiamento climatico" (climate change), "riscaldamento globale" (global warming), "effetto serra" (greenhouse effect).

indicator.[14] Table 9 proposes new estimates of Equation 3.1 made according to Specification (2) and Specification (3), both augmented with sectoral fixed effects, from 2010 to 2016. In all estimates, ClimRisk remains significant at the 1% level, with comparable coefficients across years. From the 2010's to the 2016's estimations, the Rsquared increase from 11% (16% when controlling for the value added) to 13% (19%). All in all, the results suggest that the relationship between climate-related catastrophe risk and bank lending is not born in the recent years of climate policy negotiations, but still existed years before; over time, this relationship is becoming even tighter (but at a slow pace).

4 Robustness analysis

Our municipal-level dataset does not allow us to control for bank and firm size. On the bank side, large banks may be better able to diversify risk, screen firms and absorb losses, but also have different internal decision processes and relationships with their customers; on the firm side, small and medium-sized enterprises may be less resilient to floods than

[14]ClimRisk is based on a unique 2014 mapping; however, it can be safely used to proxy climate risk exposure also in preceding and following years, provided that it is highly unlikely that few years on natural events lead single municipalities to be reclassified in different risk categories. This point is confirmed by the risk classification appeared in an updated risk mapping released in 2018, which presents only tiny variations with respect to the 2015's one.

	without $VAcom_{y-1}$		with $VAcom_{y-1}$	
	Climrisk	R^2	Climrisk	R^2
2010	-0.107^{***}	0.107	-0.097^{***}	0.158
2011	-0.117^{***}	0.114	-0.108^{***}	0.166
2012	-0.115^{***}	0.119	-0.106^{***}	0.174
2013	-0.113^{***}	0.126	-0.104^{***}	0.184
2014	-0.121^{***}	0.131	-0.111^{***}	0.192
2015	-0.122^{***}	0.130	-0.112^{***}	0.192
2016	-0.118^{***}	0.125	-0.112^{***}	0.192
Province FE	Yes		Yes	
Industry FE	Yes		Yes	

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Specifications (1) and (2) repeated for the stock of credit in different years. Clustered standard errors.

larger firms, partly because they have fewer business units and those are geographically closer to each other (so they have less scope to diversify climate risk than large firms).

We conduct a robustness analysis using credit data from a different proprietary dataset, based on supervisory reports of banks to the Bank of Italy, which allows for a wider set of controls. This dataset aggregates loans to firms at province level, imputing loans to the province in which the firm is legally resident. The province scale and the imputation by firm residence constitute two limitations of this data source. We construct a measure of climate risk at province level ($\texttt{ClimRisk}^{\texttt{prov}}$) and, by using the province-level stocks of loans, run the following regressions

$$\log(\text{loans}^{\texttt{prov}})_{h,v,r,s,q} = \beta_0 + \beta_1 \log(\text{ClimRisk})_{v,r} + \delta\, \textbf{controls}^{\texttt{prov}}_{h,v,r,s,q} + \epsilon_{h,v,r,s,q} \tag{4.1}$$

where $\{r = 1, \ldots, 20\}$ identifies the region of residence of the borrower, $\{s = 1, 2\}$ identifies the bank type (i.e., 1 = small bank, 2 = big bank, 3 = non-classified banks) and $\{q = 1, 2, 3\}$ the type of borrower (i.e., 1 = small and medium enterprises, 2 = large non-financial firms, 3 = producer households); $\textbf{controls}^{\texttt{prov}}$ are control variables in this framework.

The control variables are: (1) a firm-size dummy for small and medium enterprises (*SME*); (2) two bank-size dummies (*BigBanks* and *SmallBanks*); (3) 22 sector dummies, to disentangle differences in credit granted between provinces relating to the sectoral specialization of each province from differences due to flood risk considerations; (4) the 2013 sectoral value added for the two macro-sectors (manufacturing and services) at province level ($\log(VAManuf2013)$ and $\log(VAServ2013)$); (5) 19 regional dummies: regional characteristics (e.g., the presence or lack of specific public spending programs at regional level) can positively or negatively affect the business environment, so the propensity of banks to lend to firms that operate in that environment. Interaction terms are also included to control for possible combined effects between variables. The firm-size dummy is interacted with the bank-size ones to control for combined bank-firm characteristics; the climate risk variable is interacted with bank dummies to identify correlations between bank lending and climate risk that are limited to specific bank types (i.e., small or bigs) or firm type (i.e., small and medium-sized enterprises).

Table 10 reports the results for the specification in Equation 4.1. The regression has an R-squared of 20%, only slightly higher than those of the baseline estimates. The dummy for small and medium-size enterprises has the expected negative sign, meaning that an increase in the share of small and medium-sized enterprises is associated with a reduction in the total amount of credit outstanding; by contrast, the coefficients of the two bank-size dummies are both positive, meaning that the stock of credit granted by big banks is higher than that granted by small banks. While the coefficient of the ClimRisk variable has positive sign, climate risk is negatively correlated with bank lending when firms are small and medium-sized firms. The latter result is in line with the municipal-level analysis and could reflect the fact that the imputation of credit in the two analyses may be similar in the case of small and medium-sized firms, which are likely to have a legal residence that is close to the places in which credit is granted (and used). Assuming that the imputation of credit to large firms is also sufficiently unbiased, the joint result for the two coefficients suggest that banks take into consideration climate risk in their loan decisions only in the case the borrower is a small or medium-sized enterprise, because the latter are considered to be less resilient to natural catastrophes. Another interesting result is that ClimRisk is positively correlated with bank lending in the case of loans granted by large banks: the latter lend more to risky areas maybe because, contrary to small banks, they are able to diversify long-term risk in their portfolio and grant credit to risky applicants to increase their share in the loan market.

All in all, results from the robustness analysis strengthen the likelihood of a credit rationing story: banks are aware of long-term climate-related catastrophe risk and ration credit to firms based on their climate risk exposure; moreover, according to the province-level analysis, they would do that only in case the loan applicant is a small and medium-sized firm, which is obviously less resilient to large flood occurrences.

Dependent variable: loans_province						
Parameter	Estimate	Std Err	t Value	p-value	95% Conf Int	
Intercept	8.499	0.063	134.9	<.0001	8.376	8.623
ClimRisk_province	0.034	0.010	3.6	0.000	0.015	0.053
controls:						
SME	- 1.248	0.019	- 65.7	<.0001	- 1.286	- 1.211
BigBanks	1.801	0.022	80.9	<.0001	1.757	1.844
SmallBanks	0.260	0.021	12.2	<.0001	0.219	0.302
SME*BigBanks	- 0.917	0.025	- 36.6	<.0001	- 0.966	- 0.868
SME*SmallBanks	- 0.016	0.024	- 0.7	0.515	- 0.063	0.032
ClimRisk_province*SME	- 0.031	0.008	- 4.0	<.0001	- 0.047	- 0.016
ClimRisk_province*BigBanks	0.039	0.009	4.2	<.0001	0.021	0.057
ClimRisk_province*SmallBanks	0.007	0.009	0.8	0.449	- 0.011	0.025
log(VAmanuf2013)	0.151	0.013	11.4	<.0001	0.125	0.177
log(VAserv2013)	0.314	0.013	24.4	<.0001	0.289	0.339
Industry sector fixed effects	Yes					
Regional fixed effects	Yes					
R-square	0.2193					

Table 10: All variables refer to 2014 except value added (2013). Regression of loans (excluding NPLs) on ClimRisk, controls and interaction terms. Loans and ClimRisk are in natural logarithm. Observations are 211,870. Robust standard errors.

5 Conclusions

We make an empirical assessment of the risk borne by the Italian banking sector through its exposure to firms located in areas at risk of flooding. For this purpose, we match a new mapping of flood risk areas over Italy with proprietary bank lending data. We construct a measure of flood risk as the share of firms located in high-flood risk areas within each municipality and test whether the amount of bank credit granted to firms depends on the level of flood risk. We find that climate-related catastrophe risk has a negative effect on bank lending, and that banks' risk perception has been high even before the issue of the flood risk mapping and the rising debate on climate change. Results are also confirmed for loans granted to small and medium enterprises in a robustness analysis at the province level.

Overall, our results suggest that credit availability is not independent of one of the main sources of climate risk, opening the way to new research on the topic. Banks appear to be aware of climate-related risks: results come from an ex-ante evaluation, and hold independently on the occurrence of the catastrophe itself. Our paper is complementary to other papers in the growing literature on the connection between climate risk and banking activity being the first, as far as we know, which explores the ex-ante behavior of banks towards this risk, looking at the physical (and not policy-related) risk induced by climate change. Our analysis is made on the entire population of bank-firm relationships, not only on those existing in limited geographic areas, so results have higher external validity than those found in most analyses of natural catastrophes. Outstanding credit in risky areas is found to be substantial: the evaluation of credit at risk using climate scenarios is left as an avenue for future research.

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