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LSIs' exposures to climate change related risks: an approach to assess physical risks

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Abstract

This paper proposes an approach to estimate the impact of adverse climatic events on the profitability of small European banks (LSIs). By considering river flooding phenomena, we construct a unique database matching the information on location, frequency and severity of floods with the location and balance sheet data of institutions mainly operating in the areas where they are headquartered (territorial LSIs). We compare the performance of territorial LSIs across regions at low and high flooding risk and test for the "core lending channel" hypothesis, whereby lending to the real economy is a catalyst of physical risks. Results show that an adverse event dropping loans to households and non-financial corporations by one percentage point (pp) of total assets entails a decrease in the Return on Assets (ROA) of territorial LSIs in riskier areas by 0.01pps (~3.1%). Moreover, if all territorial LSIs were located in riskier areas, one bank out of two would report an average ROA between 0.0001 and 0.52 percentage points lower than what observed.

JEL codes: C33, G21, Q54

Keywords: Climate change, LSIs, Profitability, Dynamic panel regressions, Core Lending

Non-technical summary

The topic of how climate change might affect the performance of the financial sector has gained increasing attention in the private sector as well as in policy fora, and is urging an adequate response. This paper relates to the current debate by assessing the possible effects of climate-change related risks on the performance of European Less Significant Institutions (LSIs).

An evaluation of these risks is made difficult by the lack of information about the geographical location of customers' businesses, their collaterals and the coverage provided by insurance policies. We propose an approach that leverages on the specificity of some LSIs business models. Institutions like credit cooperative and savings banks, for instance, are by nature more linked to the territory where they are headquartered. A large share of the exposures of these LSIs towards the real economy is therefore vis-à–vis counterparts that are geographically close to the bank. Data on their lending book should then be a good approximation of the geographical concentration of exposures.

This paper takes into consideration one of the most prominent sources of physical risks, namely floods (coastal, fluvial and pluvial), since these types of adverse events are expected to rise as a result of climate change. In particular, river floods are common natural disasters in Europe and are among the most important hazards in terms of economic damage. Notably, information on location and severity of flooding phenomena over time are associated to the location information at our disposal for European LSIs. These elements are then associated to additional data regarding the banks' business model, as well as key balance sheet metrics from ITS reporting. The dataset thus constructed is unique in its structure and would allow to approximate, to a reasonable extent, the potential exposure of territorial LSIs to flood risks, working under the assumption that these banks are by definition more anchored to their territory compared to others.

We then use the database to quantify the potential effects that an increase in flood risks might have on the performance of territorial LSIs. In particular, we focus on the role played by loans to the real economy as a catalyst for the materialisation of these risks on banks' balance sheets. Results show that a decrease in loans to households and non-financial corporations over total assets by one percentage point leads to an average drop in a territorial bank's Return on Assets (ROA) by 0.007 percentage points (1.9% of the average ROA), this negative effect being even bigger for LSIs in areas subjected to more severe floods (0.011 percentage points, or 3.1% of the average ROA). Via a counterfactual experiment, we finally show that if all territorial LSIs were located in risky areas, one out of two banks in the sample would have a lower profitability, with average decreases in ROA ranging between 0.0001 and 0.52 percentage points.

1 Introduction

The topic of how climate change might affect the performance of the financial sector has gained increasing attention both in the private sector as well as in policy fora, and is urging an adequate response[1].

This paper relates to the current debate by assessing the possible effects of climate-change related risks on the performance of European Less Significant Institutions (LSIs). In particular, a special category of such risks, physical risks, refer to direct losses caused by climate events and can be classified as:

i) chronic risks (e.g., rising sea levels and increasing temperatures);
ii) occurrence of extreme weather events (e.g., heavy rainfalls and hurricanes).

Between these two types, the negative impact of extreme events is relatively easier to assess, in that the effects of chronic risks are much more gradual over time. We then focus on this specific typology of climate-related risks.

Physical risks can impact the banking sector via an increase in:

i) credit risk, stemming from the banks' exposures to households, companies and financial counterparts that can default on their obligations;
ii) market risk, deriving from sudden adverse movements in market prices;
iii) operational risk, resulting from inadequate or failing internal processes, people and systems or from external events.

Among them, credit risk is particularly relevant for those LSIs with more traditional business models (e.g., retail banks) and it can materialise via:

i) a worsening of the borrowers' repayment capacity;
ii) a direct damage to physical collaterals.

Therefore, the present analysis takes into consideration how a well-defined category of physical risks, i.e. flooding events, can affect the profitability of smaller European banks via a change in credit risk, thus fitting into a wide stream of ongoing research (Giuzio et al. (2019), Carbone et al. (2019), Schellekens and van Toor (2019), Vermeulen et al. (2018))[2].

It is commonly accepted that the materiality of physical risks is still low due to wide insurance coverage as a first line of loss absorption (ACPR (2019a,b,c)). Banks would be hit only

[1] See in this regard the European Commission's Action plan on Financing Sustainable Growth, released in March 2018 and the EBA's Action Plan on Sustainable Finance released in December 2019.

[2] In a similar vein, Sautner et al. (2020) propose an alternative approach to measure firm-level climate change exposure from conversations in the earnings conference calls.

indirectly and for the residual losses not covered by insurance policies. Nonetheless, such a statement crucially depends on the geographical composition of the banks' assets portfolios. There are indeed areas in Europe that are more exposed to climate-related physical risks and this might generate substantial issues for institutions with higher credit exposures in those areas. However, an assessment of these risks is made difficult by the lack of information about the geographical location of customers' businesses, their collaterals and the degree of coverage of insurance policies.

The approach proposed in this paper leverages on the specificity of some of the LSIs business models. Institutions like credit cooperative and savings banks, indeed, are by nature more linked to the territory where they are headquartered[3]. A large share of the exposures of these LSIs (territorial LSIs henceforth) towards the real economy (e.g. non-financial corporations and households) is therefore vis-à–vis counterparts that are geographically close to the bank. Territorial LSIs can hence represent an ideal grouping to produce a first quantitative assessment of the effects of climate-related risks.

Against this backdrop, data on their lending book should provide, to a good degree of approximation, an indication of the geographical concentration of exposures. Given this working hypothesis, the first part of the paper will focus on providing some stylized facts about the credit that these banks have towards households (HHs) and non-financial corporations (NFCs), as adverse climatic events might take a higher toll onto the repayment capacity of these counterparts, thus making them more vulnerable to physical risks. In this regard, the literature has also highlighted the negative relationship between climate-related *transition* risks and the creditworthiness of loans and bonds issued by corporates (Delis et al. (2019), Capasso et al. (2020)).

One of the most prominent sources of physical risks is given by floods (coastal, fluvial and pluvial), in that these adverse events are expected to rise as a result of climate change (BOE (2018)). In particular, river floods are a common natural disaster in Europe and are among the most important hazards in terms of economic damage. River floods can indeed provoke substantial losses deriving from direct and indirect damages to infrastructure, property, agricultural land and production[4]. Moreover, part of the existing literature has highlighted the existence of a negative relationship between flood risk exposure and lending to NFCs and HHs (Faiella and Natoli (2018), Garbarino and Guin (2020)). The first step of the analysis will then

[3] In this regard, the European Economic and Social Committee (EESC) has stated that: "[...] cooperative and savings banks offer some highly distinctive features: these include their links with the local production fabric, their firm anchorage in their region, [...], their closeness to local interests and social operators, and their solidarity" (EESC (2015)).

[4] See https://www.eea.europa.eu/data-and-maps/indicators/river-floods-3/assessment.

consist of evaluating the concentration of territorial LSIs in regions that are more exposed to severe flooding phenomena.

All the results discussed in the following sections build on the information collected about the frequency and severity of flood events in the 19 SSM countries over the period 1980-2014, as provided by the European Environment Agency (EEA)[5]. Notably, the dataset matches data on the location of the events, as well as their intensity and duration, with the locational information at our disposal for European LSIs. These elements are associated to additional data regarding the banks' business model and to the key balance sheet metrics from ITS reporting over the period 2018Q1-2019Q4[6]. The dataset thus constructed is unique in its structure, in that it approximates, to a reasonable extent, the potential exposure of territorial LSIs to flood risks, given the assumption that these banks are by definition more anchored to their territory compared to others. An additional caveat to our analysis consists of approximating the exposure to flood risks by looking at the historical occurrence of flooding phenomena, a choice motivated by the empirical regularities characterizing the observation of these events, as explained in Section 2[7].

The paper is structured along two main blocks. In the first part, we define the concept of territorial LSIs and we identify those banks for which flooding risks might be more relevant. Besides the more immediate supervisory use[8], the first part is instrumental for conducting a more structural analysis aimed at exploring how physical risks can materialise on banks' balance sheets. Notably, in Section 3 we first provide an overview of the possible mechanisms of transmissions and, then, set up a panel regression model to analyse the relationship between flood risks, lending to the real economy and LSIs profitability. We find that the "core lending channel" is more relevant for territorial LSIs than for other types of institutions and this is especially the case when taking into consideration those banks located in areas at higher flooding risk. A decrease in loans to households and non-financial corporations by one percentage point with respect to total assets leads to an average drop in a territorial bank's return on assets (ROA) by 0.007 percentage points (1.9% of the average ROA), this negative effect being even more pronounced at LSIs in areas subjected to more severe floods (0.011 percentage points, or 3.1% of the average ROA at these institutions).

We finally perform a counterfactual exercise to show that, if all territorial LSIs were located in risky areas, their profitability would be significantly lower with a probability of 50% (one out

[5] The database is being currently updated with information until 2019. Refer also to https://www.eea.europa.eu/data-and-maps for a list of publicly available datasets.

[6] The period of reference is reduced to the time span where LSIs report the complete FINREP and CoRep templates.

[7] In this regard, a report by the UK Committee on Climate Change (CCC) highlights that extreme floods like the ones experienced in UK in Autumn 2000 are to become more and more frequent in future (CCC (2016)).

[8] This list of banks can be submitted to line supervisors, who can then follow up with their respective banks and check whether an institution has adopted special strategies to internalize flood risks in its portfolio.

of two banks in the sample), with average decreases in ROA ranging between 0.0001 and 0.52 percentage points. In particular, we identify 350 banks whose ROA would drop on average by 0.17 percentage points, from 0.45% to 0.28%, and that account for around 29% of total LSI sector's assets.

2 Relating floods and banks data

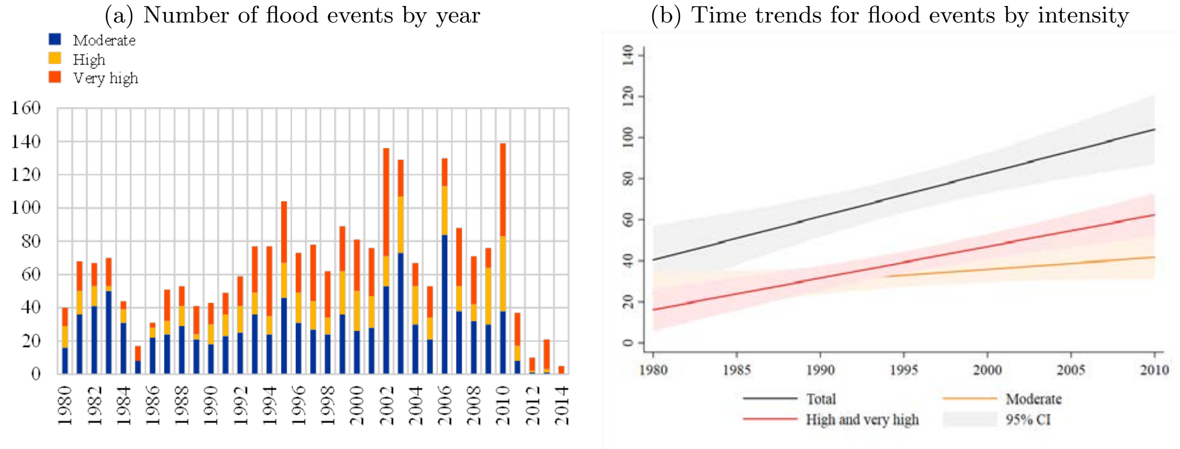
This section provides an overview of the selection algorithm deployed to identify the sample of European territorial LSIs that are more vulnerable to severe river floods. In particular, Section 2.1 analyses the flood database and describes the key features of the events. Section 2.2 then relates this information to the bank-level dataset to identify the group of banks in potentially riskier areas.

2.1 Identification of areas at higher flood risk in Europe

The first step consists of analyzing the main trends emerging from flood data, both in terms of frequency and severity, with the purpose of identifying geographical areas more subject to this risk. Figure 1a depicts the evolution of the euro area aggregate number of reported floods over time. At a first glance, the time series shows a certain degree of fluctuation in the occurrence of events, though featuring a clear upward trend which is generally more evident for the more severe episodes (Figure 1b)[9].

Figure 1: Flood events in the euro area.

(a) Number of flood events by year (b) Time trends for flood events by intensity



Source: EEA, author's computations.
Notes: Time trends are estimated over the period 1980-2010. Shaded areas represent 95% confidence bands.

Aggregate data however conceal a great degree of cross-country heterogeneity, both in terms of

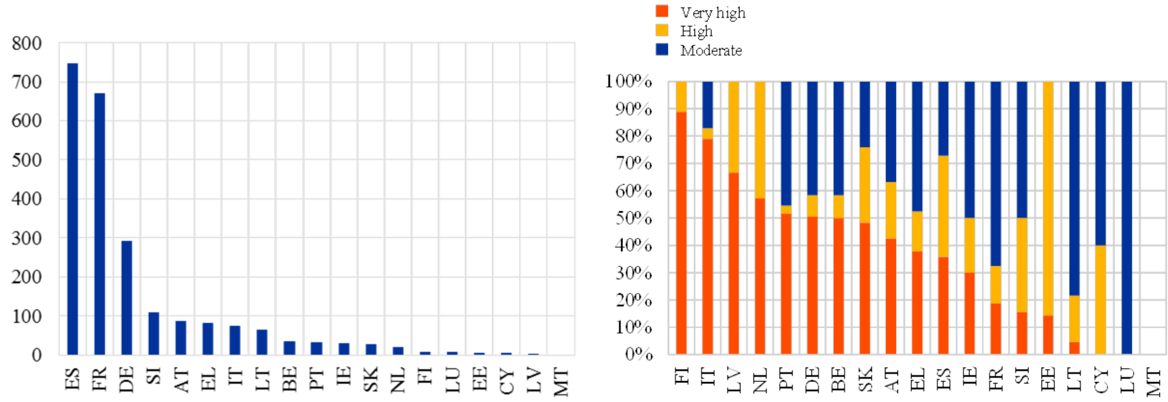
[9]Fluctuation in the number of events is also due to the different country coverage, which raises significantly after the year 2000, when first data from CEE countries became available. The database is also less complete after the year 2010, when the number of reported events falls sharply.

total number of reported events and as regards the severity of such events. For instance, large countries like France, Germany and Spain account for more than 70% of the total number of reported events (Figure 2a)[10]. Meanwhile, in countries like Finland, Latvia and the Netherlands, although the total number of events is lower, such events are particularly severe (Figure 2b). This is also the case of Italy, which is the country among the largest ones to report the lowest number of events.

Figure 2: Flood events by country.

(a) Number of flood events

(b) Intensity of flood events



Source: EEA, author's computations.

The following analysis will then take into account these differences when evaluating LSIs' activities in the different territories. In this regard, flood data are collected along the geographical classification by River Basin Districts (RBDs), rather than along the administrative boundaries. This often entails that single RBDs correspond to multiple NUTS regions. When that is the case, it is assumed that each NUTS region embedded in one RBD has been subjected to the same number of events as reported in the whole RBD.

In order to better identify the potential effects that flood risks can exert onto LSIs' credit exposure, the analysis focuses only on those areas of Europe that are particularly exposed to floods. In particular, in each country higher flood risk regions are identified as those where the number of severe events (corresponding to intensity "high" or "very high") is one standard deviation higher than the average of the country where these regions are located. This relative classification takes into account the cross-country heterogeneity in terms of reporting policies and enable to identify risk areas in each of the 19 SSM jurisdictions. The proposed approach identifies a total of 19 regions subjected to high risk and 18 exposed to very high risk, over a total of 173 regions across Europe. By the same approach, we detect 17 regions that have been subjected over time to relatively more frequent high or very high-intensity floods. A check of

[10] This is also partly due to a reporting bias, as some national agencies are more inclined to report lots of low severity events. Descriptive statistics computed only for countries that have more rigorous reporting over time (e.g., France, Germany, Italy and Spain), however, show the same trends detected with aggregate figures.

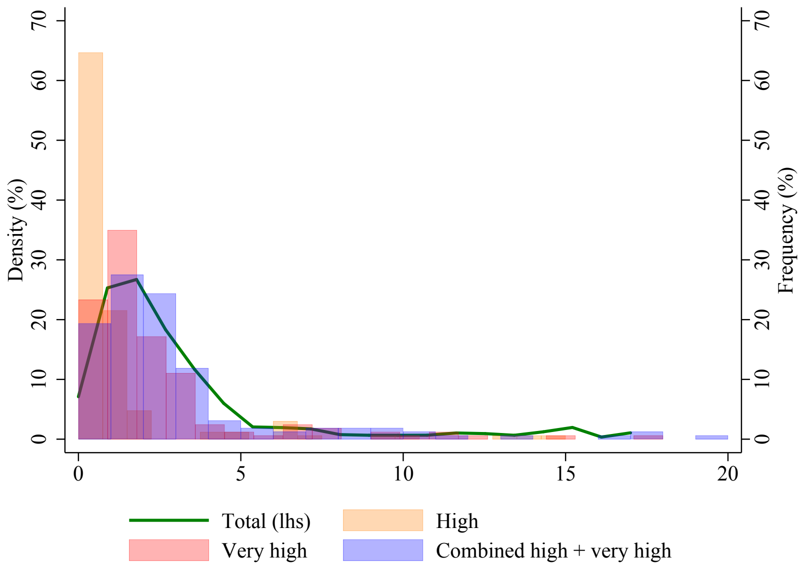
the higher-moments of the empirical distribution of flood events (Table 1), as well as a visual inspection of the kernel densities (Figure 4) show that our approach well captures the higher tail of the risk distribution.

Table 1: Descriptive statistics of flood events by intensity

	High						Very high						High and very high					
Country	(1)	(2)	(3)	(4)	(5)	**(6)**	(1)	(2)	(3)	(4)	(5)	**(6)**	(1)	(2)	(3)	(4)	(5)	**(6)**
AT	2.00	4.56	2.36	6.80	6.56	**1**	4.11	8.99	2.44	7.02	13.10	**1**	6.11	13.52	2.43	7.00	19.63	**1**
BE	0.27	0.47	1.02	2.04	0.74	**3**	1.64	2.11	1.57	4.79	3.75	**1**	1.91	2.30	1.77	5.58	4.21	**1**
CY	2.00	-	-	-	2.00	**0**	0.00	-	-	-	0.00	**0**	2.00	-	-	-	2.00	**0**
DE	0.61	1.50	3.09	12.01	2.10	**3**	3.89	9.16	3.81	17.60	13.06	**3**	4.50	10.47	3.63	15.83	14.97	**3**
EE	6.00	-	-	-	6.00	**0**	1.00	-	-	-	1.00	**0**	7.00	-	-	-	7.00	**0**
ES	14.58	30.74	2.36	7.07	45.32	**2**	14.05	19.17	1.21	2.93	33.22	**5**	28.63	47.78	1.95	5.66	76.41	**2**
FI	0.25	0.50	1.15	2.33	0.75	**1**	1.25	0.96	-0.49	1.63	2.21	**0**	1.50	1.29	0.00	1.64	2.79	**1**
FR	3.43	8.43	3.26	13.55	11.87	**2**	4.91	12.89	3.84	17.07	17.81	**2**	8.35	21.11	3.69	16.21	29.46	**1**
GR	0.92	1.26	1.20	3.59	2.18	**1**	2.38	2.63	0.99	3.03	5.02	**2**	3.31	3.54	0.69	2.20	6.85	**3**
IE	2.00	3.46	0.71	1.50	5.46	**1**	3.00	1.00	0.00	1.50	4.00	**0**	5.00	4.36	0.67	1.50	9.36	**1**
IT	0.14	0.36	2.04	5.17	0.50	**3**	2.86	2.74	2.10	7.27	5.60	**2**	3.00	2.86	2.34	8.40	5.86	**2**
LT	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**
LU	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**
LV	1.00	-	-	-	1.00	**0**	2.00	-	-	-	2.00	**0**	3.00	-	-	-	3.00	**0**
MT	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**	0.00	-	-	-	0.00	**0**
NL	0.75	0.45	-1.15	2.33	1.20	**0**	1.00	-	-	-	1.00	**0**	1.75	0.45	-1.15	2.33	2.20	**0**
PT	0.14	0.38	2.04	5.17	0.52	**1**	2.43	3.87	1.85	4.76	6.30	**1**	2.57	3.82	1.80	4.68	6.39	**1**
SI	19.00	26.87	0.00	1.00	45.87	**0**	8.50	9.19	0.00	1.00	17.69	**0**	27.50	36.06	0.00	1.00	63.56	**0**
SK	2.00	2.71	1.05	2.26	4.71	**1**	3.50	4.51	0.91	2.12	8.01	**1**	5.50	7.14	1.03	2.22	12.64	**1**
Total	2.82	11.67	7.06	57.35	14.48	**19**	4.34	9.91	3.95	19.08	14.25	**18**	7.16	20.18	5.38	36.10	27.33	**17**

Notes: (1) Mean; (2) Standard deviation; (3) Skewness; (4) Kurtosis; (5) Threshold; (6) Number of identified regions with extreme frequency.

Figure 3: Kernel density of reported events and frequency by intensity.

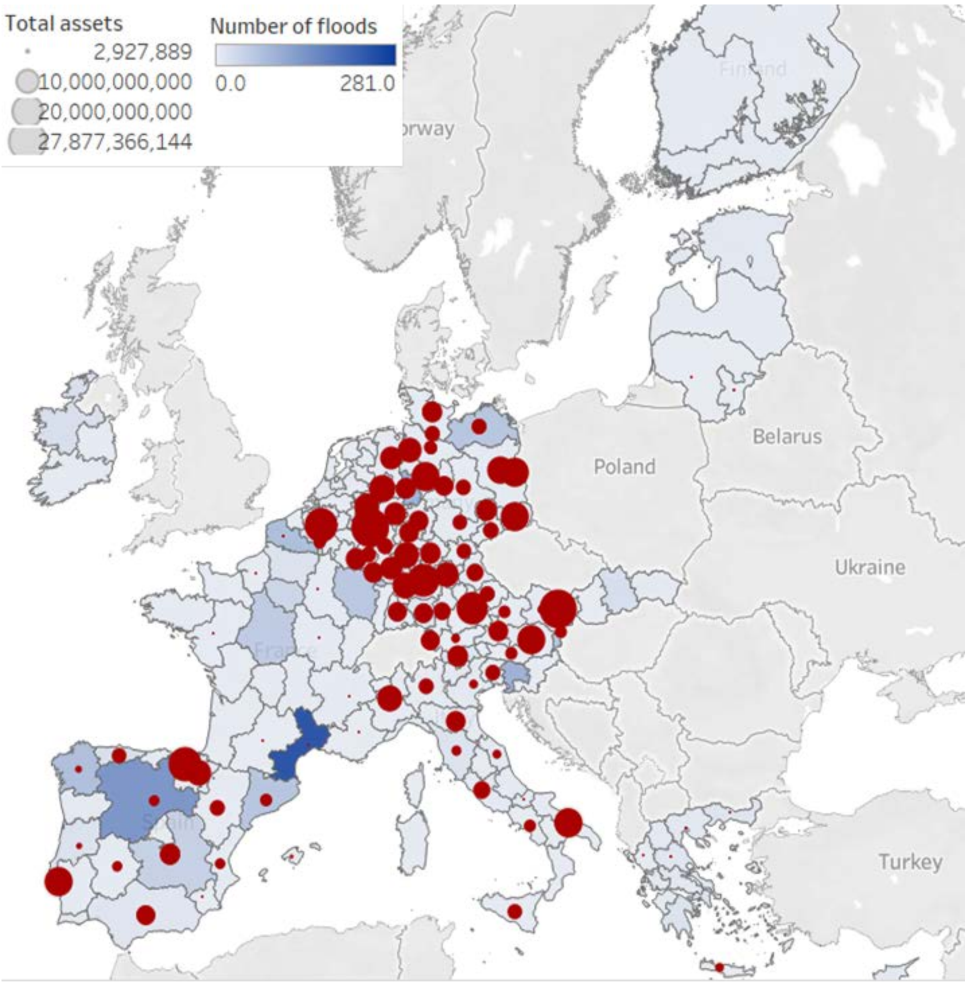


Source: Author's computations.

2.2 Identification of LSIs exposed to flood risk

The sample of European LSIs that is considered for the purpose of the paper is given by those institutions with a typically stronger territorial focus, i.e., those banks that are likely to operate in the territory where they are headquartered. This territorial focus might make institutions more vulnerable to sudden adverse flooding events in geographical areas that are more prone to these events. An example of such type of banks (territorial LSIs henceforth) is given by those LSIs operating within the credit cooperative and savings sectors[11]. All in all, 1718 LSIs are considered over 9 SSM countries, which make more than a half of the entire LSI sector in terms of total assets (64%)[12]. Among these banks, around 131 operate in areas that are particularly exposed to severe floods, as revealed by the historical records of events in those regions, while 126 LSIs are located in areas exposed to milder flooding risks. Figure 4 depicts the concentration of more severe flood episodes across the euro area, together with the location of territorial LSIs.

Figure 4: Intensity of floods by NUTS region and "territorial" LSIs.



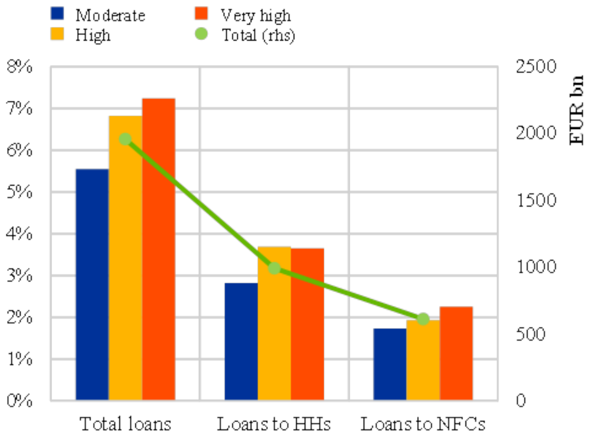
Source: EEA, ECB supervisory statistics, author's computations.
Notes: Bubbles dimension is proportional to the assets size of the related LSI.

[11] See Appendix B for more details about the selection of territorial LSIs

[12] These numbers are based on a sample of banks fixed at 2019Q4. Using a changing composition approach would enlarge the sample to 1738 institutions. The results reported in the following analyses, however, do not substantially change across the two sampling methodologies.

One of the major channels whereby these risks can affect LSIs performance is given by their credit exposure towards the real economy, especially lending to both non-financial corporations (NFCs) and households (HHs). These particular counterparts are indeed more vulnerable to a rise in the frequency and severity of floods in the regions where they operate/reside. Absent more comprehensive information on the location of counterparts, an indication of the potential exposure of territorial LSIs to risks related to flooding is provided by the amount of loans they have booked on their balance sheets towards NFCs and HHs, assuming that the geographical scope of business for these banks is circumscribed by the region where they are located[13]. Figure 5 shows aggregate figures for loan stocks to HHs and NFCs in 2019Q4 by LSIs located in regions with moderate, high and very high flooding risk. All in all, territorial LSIs operating in higher flood risk regions at the end of 2019Q4 held an amount of loans to the real sector corresponding to 4.56% of total LSIs loans to HHs and NFCs, which drops to 4.21% when considering also loans to other banks, non-bank financial corporations and the government (Table 2).

Figure 5: Share of territorial LSIs loans by flood intensity



Source: ECB supervisory statistics, author's computations.
Notes: Data refer to 2019Q4. Bars represent percentage shares of total loans, while the solid line reports total loans in EUR bn (rhs).

Table 2: Territorial LSIs in risky areas by country

Country	#	Total Loans	"Core" Loans
DE	54	4.07%	4.21%
IT	43	9.45%	10.92%
AT	23	2.60%	2.08%
ES	5	19.78%	24.09%
PT	4	1.97%	1.18%
BE	1	4.83%	5.82%
FR	1	0.07%	0.07%
Total	**131**	**4.21%**	**4.56%**

Source: ECB supervisory statistics, author's computations.
Notes: Data refer to 2019Q4. # refers to the number of banks headquartered in the identified riskier areas. Total loans include loans to HHs, NFCs, other financial corporations, banks and the government. "Core" loans refer to the amount of loans to HHs and NFCs as a share of the total.

Out of these 131 institutions, 54 are located in Germany and account for around 5% of the domestic LSI sector's loans to the real economy. The second most represented country is Italy, with 43 banks accounting for almost 15% of the domestic LSIs' loans, while the third is Austria (23 for a total 4% of domestic loans). Out of the remaining 11 banks, 5 are located in Spain

[13]Other types of assets could also be exposed to such risks, like for instance equity or traded debt of companies with large share of their operations located in or near areas subject to flood risks. However, the amounts of these assets on territorial LSIs' balance sheets are typically much inferior to loans.

and account for 10% of domestic "core" loans, 4 are in Portugal (4.2%), 2 (one each) in Belgium (18%) and France (0.14%).

3 Banks' profitability, flood exposure and the lending channel

In this section we provide some evidence on the impact of flood risks onto LSIs profitability. As mentioned in Section 1, one of the main channels of transmission of physical risks to the banking sector is given by an increase in credit risks. Such risks can have a repercussion on banks' profitability via changes in elements of the income statement. For instance, a deterioration in the borrowers' repayment capacity can entail a decrease in the net interest income deriving from a reduction in performing loans, or an increase in provisioning in anticipation of higher default probabilities. Both these instances can lead to a decrease in profits and, hence, profitability. Against this backdrop, banks headquartered in areas that are more subjected to floods might also internalize physical risks by adopting some mitigation measures aimed at increasing their loss absorption capacity (e.g., via an adjustment of their pricing schedule so to charge higher interests on loans to HHs and NFCs in those areas or via an increase in liquidity and capital buffers)[14].

Our analysis mainly focuses on the dynamics that flood risks can trigger in the profit and losses statement of territorial LSIs. The working hypothesis which our analysis rests upon is that a higher amount of exposures to HHs and NFCs at a given point in time is likely to make banks located in risky areas more vulnerable to the economic damage deriving from a severe flood. This assumption is directly derived from the peculiar characteristics of the banks we focus on, i.e. small institutions whose business is concentrated in areas surrounding their headquarters. In other words, the setup adopted in the following sections is devised to quantify the repercussions of flood risks on a well-defined category of banks, territorial LSIs, via a particular transmission channel, i.e. credit risk on the banks' balance sheet.

A more direct approach (e.g., regressing ROA on the number of past severe flooding events) would make it not possible to disentangle across different transmission channels. In addition, the historical information on river floods, while being indicative for the risk in each territory, predate the available ITS data for LSIs, which *de facto* does not allow for a straight temporal comparison between flood events and banks' performance. Nonetheless, one of the robustness checks in Appendix C.2 proposes a regression setup similar to Murfin and Spiegel (2020). Not only are the results aligned with those of the baseline regression, but we also find that including the historical number of floods among the control variables makes the coefficient on core loans

[14] On the effects of physical risks on pricing, see also Bernstein et al. (2019).

significantly higher, which further supports our assumption that flood risks take a toll onto LSIs performance mainly through core lending.

3.1 Preliminary evidence

Figure 6 depicts the distribution of the average ROA across the LSI banks in the sample. While the pooled empirical distribution of ROA (Figure 6a) at LSIs potentially more exposed to severe flooding is not significantly different compared to the other LSIs, on the other hand an analysis of the distribution over time (Figure 6b) reveals that the same institutions have reported on average a lower ROA compared to the other LSIs, though the gap between the two groupings has closed since 2019Q3. This is also reflected by the lower mean of ROA at LSIs in riskier areas (0.34%) compared to other territorial LSIs (0.37%), a difference (6%) which is statistically significant at the 1% significance level. A cross-country comparison of ROA distribution reveals that such discrepancy is mainly driven by countries like Austria, Portugal and, to a lesser extent, Germany, while the contrary holds true in Italy and Spain (Figure 6c).

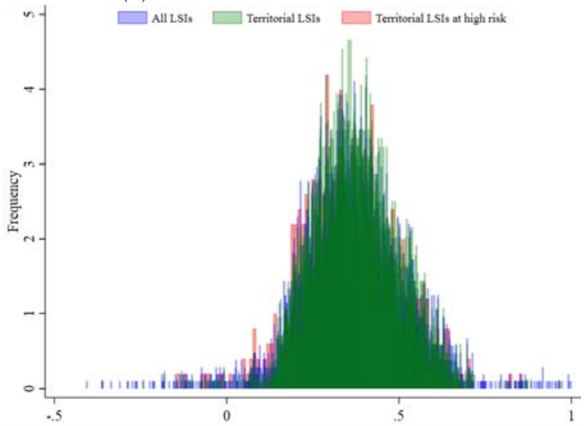
So far, empirical evidence hints at a difference in performance among territorial LSIs identified as more or less exposed to flood risks, though this cannot be interpreted as a straight causal link between flood risk exposure and profitability. Notably, it is necessary to adopt a structural approach to gauge a more precise indication of the underlying mechanisms at play.

Table 3 provides a comparison of some bank-level aggregates across territorial LSIs. The lower average ROA in areas at higher risk is generally associated with inferior lending to HHs and NFCs, lower net interest margins, higher provisions, core interest income, cost-to-income ratio and TIER1 capital ratio. These stylized facts seem to suggest that flood risks can impact profitability in two ways: i) via an increase in credit risk, as reflected by the drop in net interest margin and the increase in provisioning; ii) via the deployment of mitigation measures (e.g., more expensive pricing and greater capital buffers).

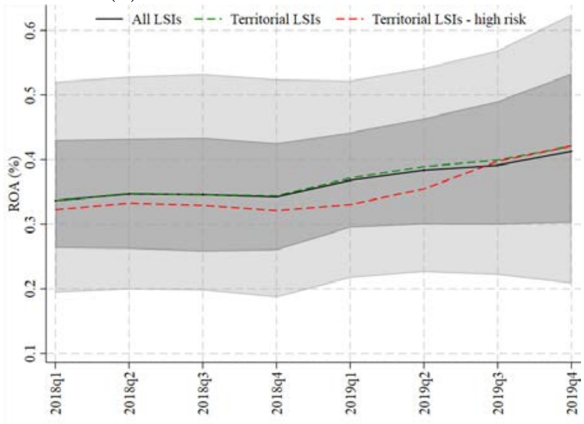
As regards the link with the amount of loans to HHs and NFCs that territorial LSIs hold on their balance sheets, a quick glance at the available data suggest that core lending has generally decreased at these institutions, in particular in 2018. However, it also looks like that the decline has been slightly more marked at LSIs located in areas at higher flood risk (see Figure 7). Moreover, Figure 8 displays the results of simple regressions of banks' ROA on the amount of loans to HHs and NFCs in the preceding quarter, at different horizons. Although this exercise does not control for the mechanisms discussed above, estimates already provide useful insights. For horizons from 1 to 4 quarters ahead, indeed, the relationship between ROA and the amount of core loans is positive and marginally more marked at those territorial LSIs belonging to the

Figure 6: Profitability at LSIs

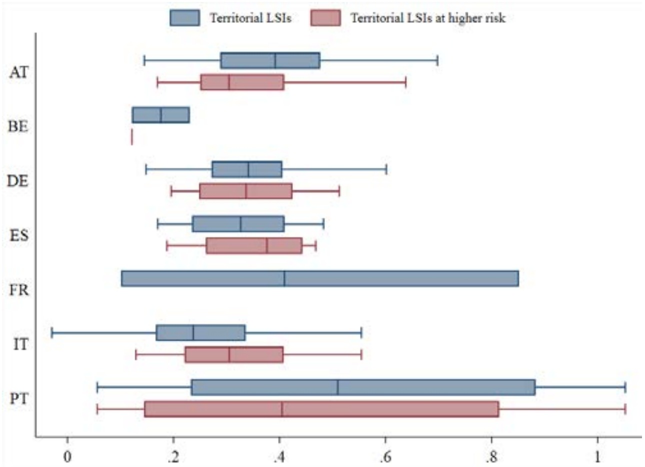
(a) Pooled distribution of ROA



(b) Distribution of ROA over time



(c) Distribution of ROA by country



Notes: charts are based on a fixed sample of LSIs that have constantly reported their balance sheet positions over the period 2018Q1-2019Q4. This explains why there are no statistics for the French riskier LSI in Figure 6c. In Figure 6b, solid lines represent medians, while shaded areas mark 16%-84% (dark gray) and 10%-90% (light gray) percentiles.
Source: ECB supervisory statistics, author's computations.

riskier batch. This seems to suggest that: i) profitability at territorial LSIs is more sensitive to changes in core lending; ii) the link is stronger for territorial LSIs in areas at higher risk of floods. This in turn would suggest that a sudden drop in the performance status of such loans due to a severe flooding would have a more pronounced impact on the ROA.

This statement, however, abstracts from any consideration regarding the possible side-effects stemming from an increase in provisions or a decrease in the net interest income, as well as the impact of the mitigation measures[15]. We therefore explore this "core lending channel" in

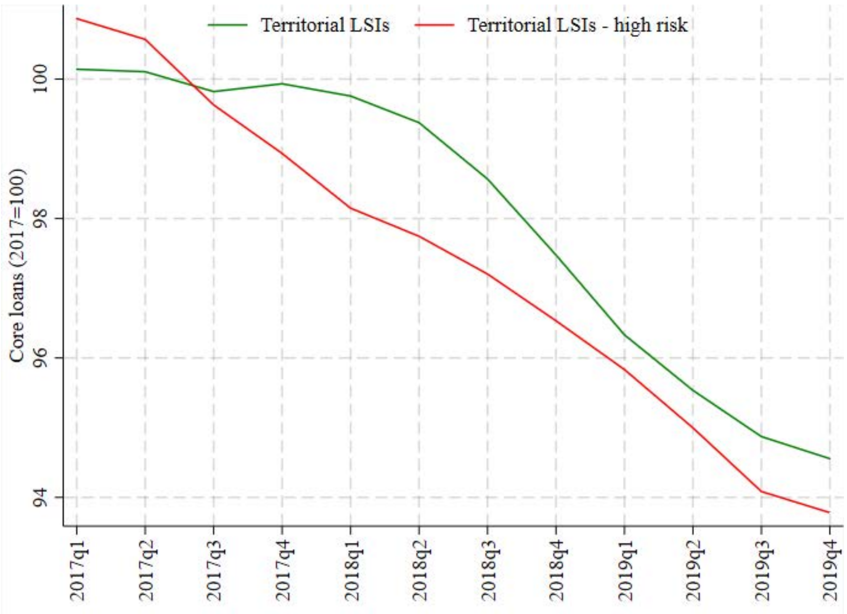
[15] Provisioning is one of the first lines of defense for banks to internalize shifts in risks, especially credit risks. For this reason, part of the banking literature takes provisions as the main variable of interest. However, such approach is not particularly suitable for the LSIs we focus on, in that most of them belong to jurisdictions (e.g., Germany and Austria) where the accounting framework allows to substitute provisions on the income statement with capital buffers (hidden reserves) that are not directly reported on the balance sheet. This in turn entails an artificially low level of provisions that is not commensurate to the real on-balance-sheet risks, thus making it difficult to perform a meaningful analysis of the link between lending and provisioning.

Table 3: Averages of bank-level variables at territorial LSIs

Variable	Territorial LSIs at low risk	Territorial LSIs at high risk
ROA (%)	0.37	0.34
Total assets (log)	20.19	20.01
Core loans (%)	62.21	55.10
Net Interest Margin[1](%)	1.04	0.99
Provisions (%)	0.00	0.01
Core interest income[2](%)	92.97	96.22
Cost-to-income ratio[3](%)	66.89	70.04
NPL ratio[4](%)	2.49	3.91
TIER1 capital ratio (%)	17.08	18.60

Notes: [1] Net interest margin is given by the ratio of net interest income over total assets; [2] Core interest income is computed as the ratio between the interest income originated by loans and advances to HHs and NFCs and the interest income from all loans and advances; [3] Cost-to-income ratio is defined as total operating costs over total operating income; [4] the NPL ratio is given by the amount of non-performing loans divided by the total amount of loans.
Sources: ECB supervisory statistics, author's computations.

Figure 7: Evolution in core lending at LSIs



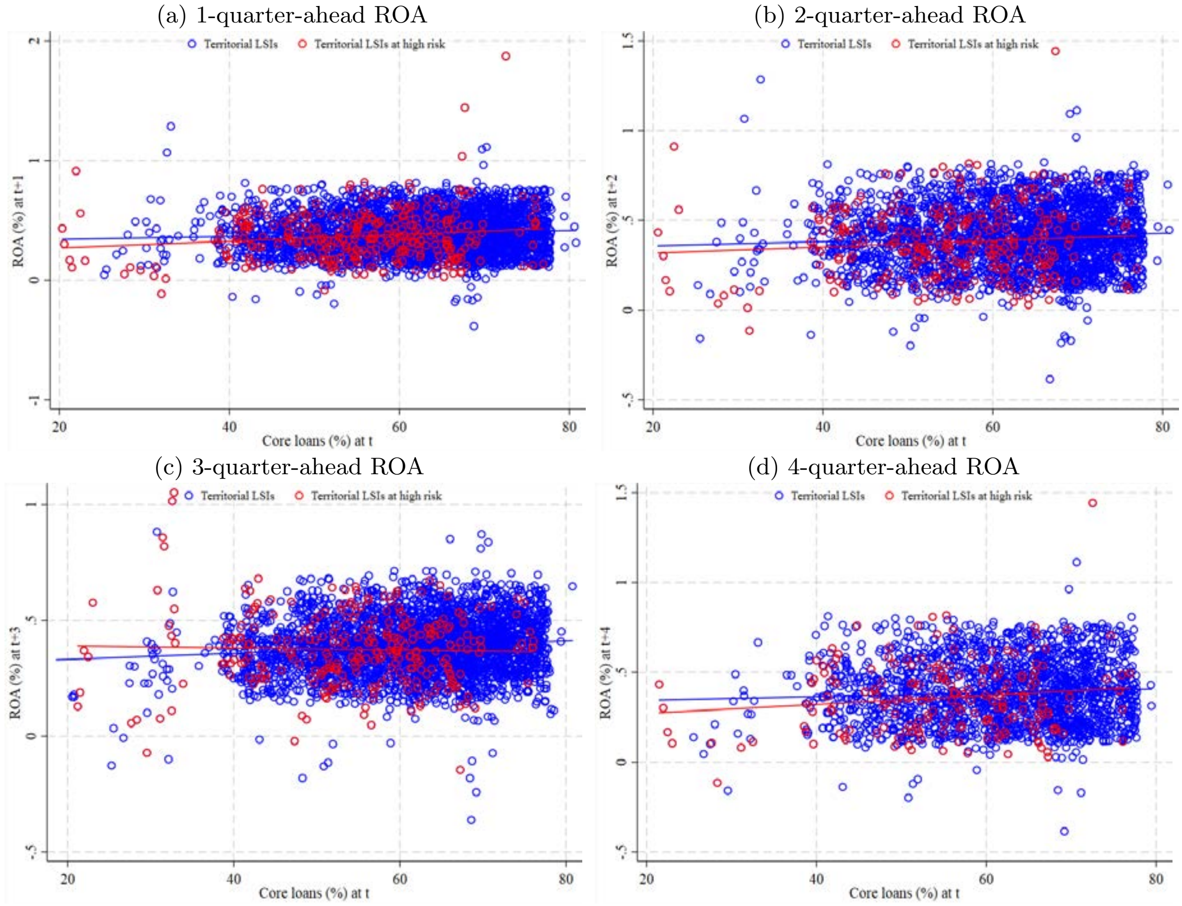
Notes: yearly moving averages indexed with 2017 = 100.
Source: ECB supervisory statistics, author's computations.

Section 3.2 below, by constructing a regression framework which is suitable to cater for all these dynamics.

3.2 Econometric analysis

Drawing from the preliminary evidence provided in Section 3.1, in this section we set up a structural econometric framework to assess the potential implications that a higher exposure

Figure 8: Relationship between ROA and core loans



Notes: charts are based on a fixed sample of LSIs that have constantly reported their balance sheet positions over the period 2018Q1-2019Q4. The fitted lines are based on linear regressions.
Source: ECB supervisory statistics, author's computations.

to flooding risks might entail for the performance of territorial LSIs, with a focus on the core lending channel[16]. In particular, we construct a model of bank profitability, which is expanded to control for the exposure to flooding risks.

Specifically, we consider a dynamic panel econometric model of the following form:

$$P_{i,j,t} = \alpha_i + \phi_j + \gamma P_{i,j,t-1} + \beta_1 \Lambda_{t-1} + \beta_2 \Sigma_{j,t-1} + Z_{i,j,t-1}\Phi + X_{j,t-1}\Psi + \varepsilon_{i,j,t} \tag{1}$$

where $P_{i,j,t}$ is ROA for bank $i = 1, \ldots, N_b$, in country $j = 1, \ldots, N_c$ at time $t = 1, \ldots, T$. Moreover, α_i and ϕ_j are bank- and country-fixed effects respectively, Z is a matrix of bank-specific (micro) characteristics, X includes country-level macro-financial and banking sector indicators, whereas Λ_t and $\Sigma_{j,t}$ are the short-term interest rate and the (country-specific) curvature of the yield curve respectively. Micro indicators control for a bank's solvency position and credit

[16] In what follows and to make the panel dataset balanced, we restrict the sample of LSIs to those banks that have always reported their balance sheet positions over the period 2018Q1-2019Q4. This reduces the number of territorial LSIs to 789.

risk related to asset quality. Macro-financial and banking sector variables, on the other hand, are needed to control for patterns in LSIs performance that are driven by the procyclicality of lending and provisioning, which ultimately affect a bank's profitability performance, thus helping alleviate potential omitted-variable biases. In addition, the inclusion of country-fixed effects is warranted to avoid potential omitted variable biases stemming from time-invariant cross-country differences. For instance, the legal framework which banks operate in can substantially change across jurisdictions. This in turn might somewhat affect the transmission of flood risks to banks' profitability through the core lending channel[17].

The model draws from the rich literature aiming at identifying the main drivers of banks' profitability[18]. In particular, variations of Equation (1) have been used to assess the pass-through of monetary policy onto the performance of the banking sector, especially in the context of the low-for-long environment and the pressure it is exerting on banks' interest margins (e.g., Borio et al. (2017) and Altavilla et al. (2018)). A specification similar to the one here adopted has been used by Lang and Forletta (2020) to analyse the impact of cyclical systemic risk on bank profitability.

As a first step, we estimate Equation (1) by disentangling between the territorial LSIs and the rest of the LSI sector Section 3.2.1. We then expand this baseline setup so to account for the potential exposure to flooding risks, as proxied in Section 2. Notably, we proceed along the following two steps:

1) we split the LSI sample into two subsamples, one including the 1718 territorial LSIs and another with the remaining LSIs (Section 3.2.1);
2) we augment the right-end-side of Equation (1) to include a dummy variable which takes value 1 if a bank belongs to the sample of territorial LSIs at higher risk and 0 otherwise. We also interact the dummy with other regressors to capture the effects that flood risks have on the main determinants of profitability (Section 3.2.2).

Table C.2 reports the list of the main variables used to estimate Equation (1), together with their statistics[19]. Bank-specific variables include: the (log) total assets to capture the effect that banks' size has on profitability (Demirgüç-Kunt and Huizinga (1999), Kok et al. (2015), Lang and Forletta (2020)), the NPL ratio to control for the quality of assets, the cost-to-income ratio to control for efficiency (Kohlscheen et al. (2018), Altavilla et al. (2018)), the TIER1 capital ratio to control for the solvency position of the bank, as well as the higher costs associated to capital

[17]For example, German and Austrian banks make use of an accounting framework, the nGAAP, which presents relevant discrepancies compared to the standard adopted in the rest of the euro area (i.e., IFRS9). This plays an important role when comparing banks' performance, especially when it comes to the evaluation of provisioning.

[18]See, among others, Kok et al. (2015) and Kohlscheen et al. (2018), as well as sources cited therein

[19]Refer to Appendix C.1 for a description of data sources

(Demirgüç-Kunt and Huizinga (1999), Altavilla et al. (2018), Lang and Forletta (2020))[20]

The set of macro-financial indicators consists of: indicators of the monetary policy stance, i.e. the (euro area wide) short-term interest rate as proxied by the 3-month OIS rate and the country-specific slope of the yield curve; indicators of the financial cycle, i.e. the VIX and the y-o-y growth of equity prices; indicators of the business cycle, i.e. yearly real GDP growth and inflation; features of the banking sector that are relevant for banks' profitability, i.e. credit to GDP ratio and the Herfindahl index for total assets (Demirgüç-Kunt and Huizinga (1999), Albertazzi and Gambacorta (2009), Borio et al. (2017), Altavilla et al. (2018)).

As mentioned earlier the dependent variable in Equation (1) is ROA. In this regard, half of the sampled banks have reported on average a ROA between 0.28% and 0.46% over the period 2018Q1-2019Q4. Meanwhile, 50% of the same LSIs have reported an average amount of core loans between 52% and 69% of total assets over the same period.

Table 4: Descriptive statistics of regression variables

Variable	Mean	St. Dev.	Skewness	Kurtosis	p25	p50	p75	N
Macro-financial								
Short-term rate[1](%)	-0.38	0.04	-1.57	4.05	-0.38	-0.36	-0.36	7480
Yield curve slope[2](basis points)	84.70	46.11	0.89	3.92	41.60	83.60	108.90	7304
VIX (log)	2.78	0.22	0.84	2.78	2.62	2.75	2.89	7480
Real GDP growth (%)	1.39	1.00	1.88	12.08	0.62	1.15	2.13	7480
Inflation (%)	0.21	0.90	1.31	5.76	-0.42	0.16	0.41	7480
Banking sector								
Credit/GDP[3](%)	40.10	4.83	1.88	14.50	37.54	39.08	40.69	7320
Herfindahl Index for total assets	0.04	0.04	3.10	13.46	0.02	0.03	0.04	7480
Bank-specific								
Total assets (log)	20.30	1.43	0.15	2.46	19.19	20.25	21.34	7480
Core loans (%)	59.11	13.86	-1.39	5.72	52.42	61.73	68.93	6285
Return on Assets (%)	0.37	0.18	1.06	30.83	0.28	0.36	0.46	7480
NPL ratio (%)	2.68	2.75	3.52	20.28	1.22	1.99	3.06	6427
Cost-to-income ratio (%)	66.89	15.52	2.68	54.08	59.17	66.68	73.53	7060
TIER1 capital ratio (%)	17.08	4.66	3.75	29.90	14.29	15.96	18.39	6235

Notes: [1] 3-month OIS rate; [2] 10-year sovereign yield - 2-year sovereign yield; [3] Defined as total loans to domestic counterparts excluding MFIs. Data coverage: 2018Q1-2019Q4.

3.2.1 Baseline regression

We first estimate Equation (1) for all the institutions in the sample and for territorial LSIs separately. The choice of the estimation technique depends on the features of both Equation (1) and the data used. The presence of the lagged dependent variable among the regressors, indeed, poses an issue of endogeneity (the so-called Nickell bias), whereas the reduced time dimen-

[20] We have also expanded the regression framework to include all the variables reported in Table 3. While results are robust, the additional variables (net interest margin, provisions, core interest income) are not generally significant and the gain in terms of explanatory power is negligible compared to the loss of information deriving from the lack of datapoints for many banks.

sion might bias the estimation using more standard approaches (e.g., fixed-effect OLS). The Arellano-Bond (1991) methodology, which makes use of lagged differenced regressors to control for the endogeneity, would provide the best solution to the first problem. However, the fact that the length of the time series is reduced with respect to the cross-sectional dimension ($N_b >> T$) makes other approaches, like the Blundell-Bond (1998) estimator, more suitable in this case[21]. We therefore adopt the latter estimation approach. Specifically, the GMM instruments for the lagged dependent variable on the right-end-side of Equation (1) are given by lags of both the dependent variable and of the other bank-specific regressors. The macro-financial variables, on the other hand, are used as IV-type instruments. Table 5 below reports results across different model specifications. Regressions that do not account for the dynamic structure of the panel (notably, OLS regressions with different types of fixed effects) produce biased estimates that can either hide the significance of important variables (e.g. core loans) or, to a more severe extent, lead to coefficients whose sign is at odds with common economic theory and the banking literature (e.g. the negative sign on short-term interest rates in the time-country fixed-effect specification). The GMM estimator in the variant of Blundell-Bond (1998) is then the most well-suited methodology in the present case and will be adopted as the baseline approach.

A closer look at the results shows a certain degree of time persistence of ROA at LSIs, as the coefficient on its own lag is significant and equal to 0.484. This also holds at territorial LSIs, where the same estimate is equal to 0.42, thus suggesting that LSIs profitability follows a somewhat steady pattern over time. As to the other coefficients, the larger and significant estimates for both GDP growth and inflation imply that the profitability of territorial LSIs is more tied to their country's business cycle, whereas the sensitivity to the financial cycle is more homogeneous across the two groupings.

As to bank-specific controls, coefficients for total assets are generally not significant, which seems to indicate that there is not a strong link between banks' size and profitability[22].

In regard to core lending, this channel seems fairly relevant at all LSIs. In particular, the estimates show that an increase in core lending with respect to total assets by one percentage point at territorial banks would lead to an increase in the ROA by an average of ~0.007 percentage points, or 1.9% of the average ROA in the sample. Therefore, an adverse climatic event like a flood, triggering a deterioration in the repayment capacity of HHs and NFCs and, hence, a reduction in performing core loans, would impact territorial LSIs profitability marginally more than at other banks.

[21] See Flannery and Hankins (2013) for an assessment of the performance of the various estimators.

[22] Some additional robustness checks are reported in Appendix C.2 to better investigate the relationship across size, profitability and flood risk.

3.2.2 Accounting for flood risks

In Section 3.2.1 we have provided evidence of a stronger linkage between profitability and core lending at territorial LSIs. We now take a step further and assess whether there is a significant change in such relationship across banks located in areas at lower and higher risk of flooding. Given the much reduced number of territorial LSIs in riskier areas compared to the rest of the sample, we control for the potential exposure to flood risks by augmenting the right end side of Equation (1) as follows:

$$P_{i,j,t} = \alpha_i + \phi_j + \delta D_i + \gamma P_{i,j,t-1} + \beta_1 \Lambda_{t-1} + \beta_2 \Sigma_{j,t-1} + Z_{i,j,t-1}\Phi + X_{j,t-1}\Psi + [D_i \times Z_{i,j,t-1}]\Xi + [D_i \times X_{j,t-1}]\Theta + [D_i \times \Upsilon_{j,t-1}]\Omega + \varepsilon_{i,j,t} \tag{2}$$

where D_i is a dummy equal to 1 if bank i is located in regions at higher flood risk and 0 otherwise, while $\Upsilon_{j,t} = [\Lambda_t \quad \Sigma_{j,t}]$ from Equation (1) above.

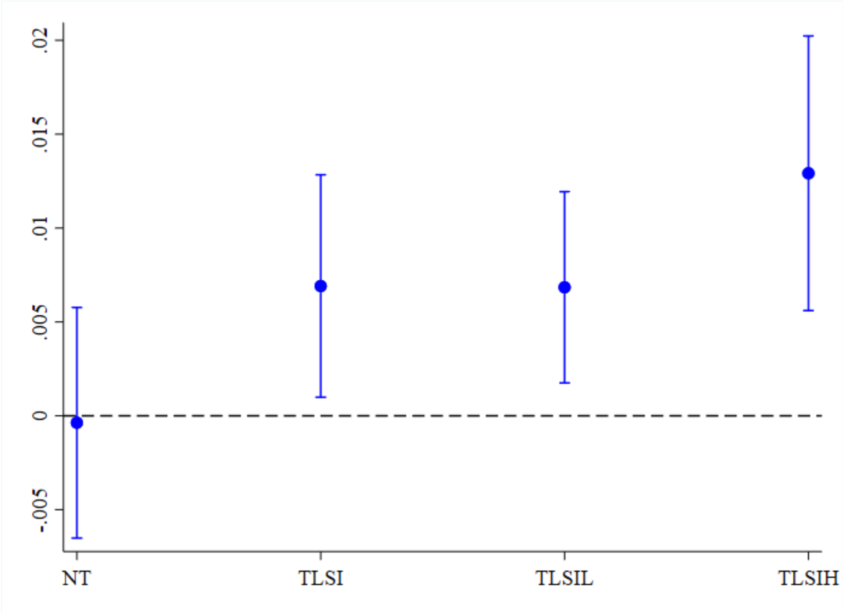
Estimation results of Equation (2) are reported in Table 6. Compared to other territorial LSIs, banks' profitability in regions exposed to flooding phenomena is more linked to the country's credit cycle rather than its financial cycle, as indicated by the significant coefficients on both credit-to-GDP and the Herfindahl Index for the banking sector. Furthermore, the coefficient on core loans is 0.011 percentage points (3.1% of the average ROA in the sample), whereas the same coefficient is 60% lower at LSIs out of the risk areas (Figure 9). This suggests that the pass-through of core lending onto ROA is significantly stronger at territorial LSIs that are exposed to flood risks[23].

In light of the results discussed so far, and to get a better sense of the difference in profitability performance deriving from flood risks, we run a counterfactual simulation where the estimated parameters of Equation (2) are fitted to the real ROA figures reported by *all* territorial LSIs. In this way, we provide an indication of what the profitability of these banks would be if all of them were located in areas that are subjected to severe floods more frequently, given the stronger impact that these events have on banks' performance through changes in the amount of core lending.

Figure 10 depicts the empirical distribution of the real ROA and the ROA implied by the coefficients of Equation (2) above (Figure 10a), as well as the empirical distribution of the differences between the two (Figure 10a). Results of the counterfactual exercise show that ROA at territorial LSIs would be on average lower if they were all located in regions at higher risk of floods. *Ceteris paribus* there exists a 50% probability for a territorial LSI to report a ROA

[23] These results are robust to several checks that control for bank-level heterogeneity (Appendix C.2).

Figure 9: Marginal effects on ROA of a one percentage point increase in core loans



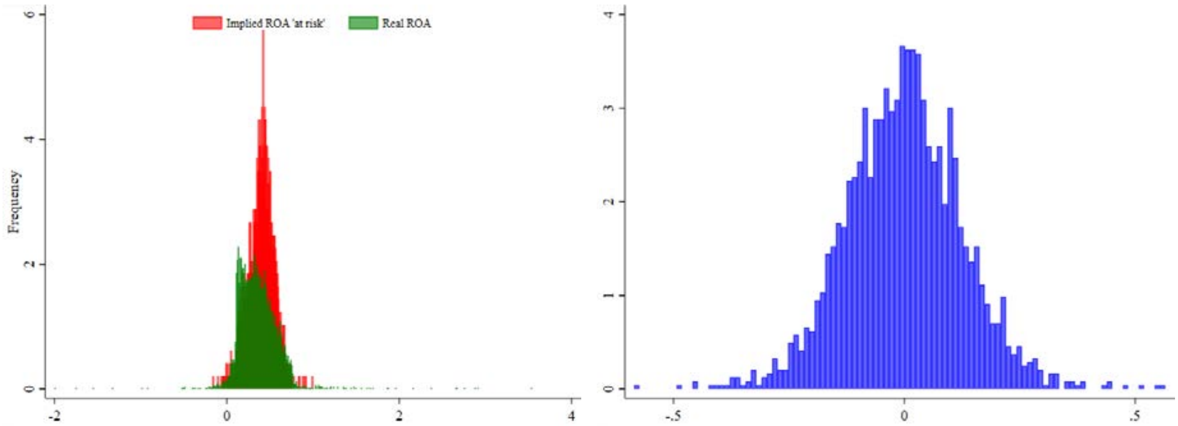
Notes: NT: non-territorial LSIs; TLSI: territorial LSIs; TLSIL: territorial LSIs at low risk; TLSIH: territorial LSIs at high risk. Charts are based on coefficient estimates of Equation (2). Whiskers represent 90% confidence bands.
Source: ECB supervisory statistics, author's computations.

that would be between 0.0001 and 0.59 percentage points lower compared to the real figures. In other words, under the alternative scenario, one out of two institutions in the sample would record a worse profitability performance.

Figure 10: Counterfactual simulation

(a) Empirical distributions of real and counterfactual ROA

(b) Empirical distribution of differences between real and counterfactual ROA



Notes: charts are based on coefficient estimates of Equation (2).
Source: ECB supervisory statistics, author's computations.

As displayed in Table 7, territorial LSIs that would report a lower ROA are 350, accounting for around 17% of total LSI sector assets. Specifically, if all these banks were located in areas subjected to higher flood risk, their ROA would on average drop from 0.48% to 0.38%.

Most of these banks are located in Germany (256 accounting for 25% of total assets) and Austria (60 accounting for 13% of total assets). The third country in terms of number is Spain (14, 18%), followed by Italy (13, 9%), France (3, 0.08%) and Portugal (4, 26%). As regards the difference between the two scenarios, Portuguese banks would be the ones most penalised (-0.19 percentage points), followed by French LSIs (-0.14 percentage points) and Austrian institutions (-0.10 percentage points). Territorial LSIs in Italy, on the other hand, would be the least affected, with an average decrease of 0.08 percentage points.

4 Concluding remarks

In the context of the ongoing debate on climate-related risks and their materialisation in the financial sector, this paper proposes an approach to assess the potential impact of physical risks on the performance of European LSIs.

By focusing on a particular category of such risks, namely flood risks, we exploit the peculiarities of the LSI business models to proxy the location of the banks' counterparts. We focus on those institutions that tend to operate exclusively in the regions where they are headquartered, which we name "territorial LSIs". We then link the location of territorial LSIs to the historical occurrence of floods in the same area, thus identifying those banks that might be more exposed to flood risks.

We use this unique dataset to assess the potential impact of higher flood risks on LSIs performance. In particular, we provide evidence that ROA has been on average lower at banks located in areas that have been historically more subjected to severe flooding events and this is partially due to the so-called "core lending channel" of transmission, whereby flood risks can hinder banks' profitability via the decrease in lending to HHs and NFCs.

All in all, while the approach proposed in this paper relies on a series of assumptions that are nonetheless supported by observational evidence, the results discussed can be used as guidance for the exploration of more granular information that are becoming available (e.g., Anacredit). In addition, the selection algorithm developed in the first part could be easily adapted to other types of climatic events, where data are made available[24].

[24] A venue for future research could for instance consist of expanding the risks database to encompass projections of floods as well as droughts. See: https://www.wri.org/publication/aqueduct-floods-methodology).

Table 5: Baseline regression with different estimators

Dep. Variable = ROA_t	All LSIs				Territorial LSIs
	Macro	Time-country FE	Bank-time FE	System GMM	System GMM
Regressors					
ROA_{t-1}		0.580***	0.191***	0.484***	0.420***
		(0.0613)	(0.0382)	(0.0556)	(0.0382)
Short-term $rate_{t-1}$	2.466***	-6.621***	1.936***	0.316	-0.379
	(0.256)	(0.235)	(0.301)	(0.429)	(0.329)
Yield curve $slope_{t-1}$	-0.000604***	0.00246***	0.000330	-0.00108***	-0.000105
	(0.000143)	(0.000438)	(0.000256)	(0.000224)	(0.000284)
VIX_{t-1}	1.535***	-1.007***	1.354***	-0.241***	-0.200***
	(0.0856)	(0.0219)	(0.122)	(0.0155)	(0.0198)
Equity price $growth_{t-1}$	0.000227	-0.0138***	-0.000690	0.00650***	0.00634***
	(0.000654)	(0.00477)	(0.000699)	(0.000653)	(0.000521)
Real GDP $growth_{t-1}$	0.0182	-0.113***	-0.00860	0.0391***	0.0457***
	(0.0111)	(0.0111)	(0.00851)	(0.00851)	(0.00822)
$Inflation_{t-1}$	-0.0105	0.0700***	-0.00558	-0.0206***	-0.0624***
	(0.00641)	(0.0125)	(0.00592)	(0.00630)	(0.0150)
$Credit/GDP_{t-1}$	-0.00237	-0.451***	-0.00624	0.00179	0.00752
	(0.00215)	(0.0155)	(0.00416)	(0.00471)	(0.00875)
Herfindhal $Index_{t-1}$	0.0909	91.47***	-2.032	-3.709***	-0.836
	(0.275)	(2.652)	(1.557)	(1.379)	(4.598)
Total $assets_{t-1}$		-0.00804***	-0.0432	0.0308	-0.00216
		(0.00288)	(0.0535)	(0.0438)	(0.0286)
Core $loans_{t-1}$		**0.000193**	**-0.000206**	**0.00741***	**0.00691***
		(0.000373)	**(0.00180)**	**(0.00440)**	**(0.00361)**
Cost-to-income $ratio_{t-1}$		-0.00144***	-0.000939***	-0.00157**	-0.00182***
		(0.000353)	(0.000273)	(0.000640)	(0.000672)
NPL $ratio_{t-1}$		0.00275	-0.0101*	0.00307	-0.00630
		(0.00234)	(0.00546)	(0.00786)	(0.00937)
Regulatory capital $ratio_{t-1}$		0.000593	-0.0120**	0.00111	0.00413
		(0.00122)	(0.00563)	(0.00524)	(0.00874)
$Constant_{t-1}$	-2.680***	5.316***	-1.018	0.694	0.0299
	(0.210)	(0.202)	(1.145)	(1.073)	(0.693)
Observations	4,662	2,793	2,793	2,793	2,363
Number of banks	666	515	515	515	436
Bank FE	No	No	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	No	No
R^2	0.406	0.632	0.521	0.386	0.461

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The model "Macro" is estimated by OLS with country and time fixed effects. The model "Time-country FE" includes bank-specific controls. The model "Bank-time FE" replaces country fixed effects with bank fixed effects, while The "System GMM" model uses bank fixed effects. For the system GMM estimator, the p-values of AR(1) and AR(2) tests are: i) 0.00 and 0.42 in the regression for the whole sample; ii) 0.00 and 0.14 in the regression for territorial LSIs only.

Table 6: Baseline and dummy regressions for territorial LSIs

Dep. Variable = ROA_t	All LSIs	Territorial LSIs All	Territorial LSIs Lower risk	Territorial LSIs Higher risk
Regressors				
ROA_{t-1}	0.484***	0.420***	0.439***	0.439***
	(0.0556)	(0.0382)	(0.0387)	(0.0387)
Short-term $rate_{t-1}$	0.316	-0.379	-0.0368	-0.426
	(0.429)	(0.329)	(0.372)	(0.987)
Yield curve $slope_{t-1}$	-0.00108***	-0.000105	-7.17e-05	0.000
	(0.000224)	(0.000284)	(0.000348)	(0.001)
VIX $_{t-1}$	-0.241***	-0.200***	-0.174***	-0.315***
	(0.0155)	(0.0198)	(0.0205)	(0.039)
Equity price $growth_{t-1}$	0.00650***	0.00634***	0.00744***	-0.001
	(0.000653)	(0.000521)	(0.000589)	(0.002)
Real GDP $growth_{t-1}$	0.0391***	0.0457***	0.0430***	0.051
	(0.00851)	(0.00822)	(0.00864)	(0.035)
$Inflation_{t-1}$	-0.0206***	-0.0624***	-0.0701***	-0.016
	(0.00630)	(0.0150)	(0.0145)	(0.017)
$Credit/GDP_{t-1}$	0.00179	0.00752	0.00628	0.029**
	(0.00471)	(0.00875)	(0.00897)	(0.012)
Herfindhal $Index_{t-1}$	-3.709***	-0.836	-1.420	-4.303**
	(1.379)	(4.598)	(4.261)	(1.942)
Total $assets_{t-1}$	0.0308	-0.00216	-0.00988	-0.008
	(0.0438)	(0.0286)	(0.0293)	(0.036)
Core $loans_{t-1}$	**0.00741***	**0.00691***	**0.00684****	**0.011****
	(0.00440)	**(0.00361)**	**(0.00311)**	**(0.005)**
Cost-to-income $ratio_{t-1}$	-0.00157**	-0.00182***	-0.00207***	-0.002*
	(0.000640)	(0.000672)	(0.000751)	(0.001)
NPL $ratio_{t-1}$	0.00307	-0.00630	-0.0176*	0.004
	(0.00786)	(0.00937)	(0.00995)	(0.018)
TIER1 $ratio_{t-1}$	0.00111	0.00413	0.00276	0.011
	(0.00524)	(0.00874)	(0.00502)	(0.009)
$Constant_{t-1}$	0.694	0.0299	0.469	-1.819
	(1.073)	(0.693)	(0.646)	(1.328)
Observations	2,793	2,363	2,363	2,363
Number of banks	515	436	436	436
Bank FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
R^2	0.386	0.461	0.464	0.464

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates in the last column are computed as the sum of the coefficients on regular regressors plus the coefficients on the interaction terms in Equation (2), while the constant is given by $\hat{\alpha}_i + \hat{\delta}$ from the same Equation. For the system GMM estimator, the p-values of AR(1) and AR(2) tests are: i) 0.00 and 0.42 in the regression for the whole sample; ii) 0.00 and 0.14 in the regression for territorial LSIs only; iii) 0.00 and 0.14 in the regression for territorial LSIs at high risk.

Table 7: Territorial LSIs with lower ROA in the counterfactual exercise

Country	#	ΔROA (pps)	Share of assets
DE	256	- 0.10	24.64%
AT	60	- 0.10	13.27%
ES	14	- 0.09	17.63%
IT	13	- 0.08	9.21%
PT	4	- 0.19	25.50 %
FR	3	- 0.14	0.08%
Total	**350**	**-0.10**	**16.77%**

Notes: ΔROA is the difference between the real and the counterfactual average ROA. Total assets are expressed as percentage shares of the total assets at domestic LSIs.

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Appendix

A Matching floods location with banks location

The first building block of the dataset is given by historical data on European floods covering the years between 1980 and 2014, which are based on the reporting of EU Member States under the EU Flood Directive (2007/60/EC). Such data have been collected by the European Environment Agency and complemented with additional information as provided by the single national authorities.

Specifically, data are organized by single flooding events, each associated to a unique identifier which allows linking a specific event to its location, duration and severity, thus making the reported information very detailed. Figure A.1 below provides an example of how the dataset is structured.

Figure A.1: Structure of floods database

Country	Year	StartDate	EndDate	Duration (days)	Flood ID	Flood location	RBD code	Severity	Source
AT	1997	05/07/1997	09/07/1997	21	AT-1997-07-05	Traisen (Fluss-km 58,5 bis 72)	AT1000	Very High	EM-DAT
BE	2005	10/09/2005	11/09/2005	1	BE-2005-09-10	Vilvorde, Diegem, Louvain, La Roche-en-Ardenne (Luxemburg), Brabant Wallon, Hainaut	BE_Escaut_BR	Moderate	EM-DAT
ES	2013	18/06/2013	19/06/2013	2	ES-2013-06-18	Aran Valley (Huesca and Lleida provinces)	ES091	Moderate	EM-DAT

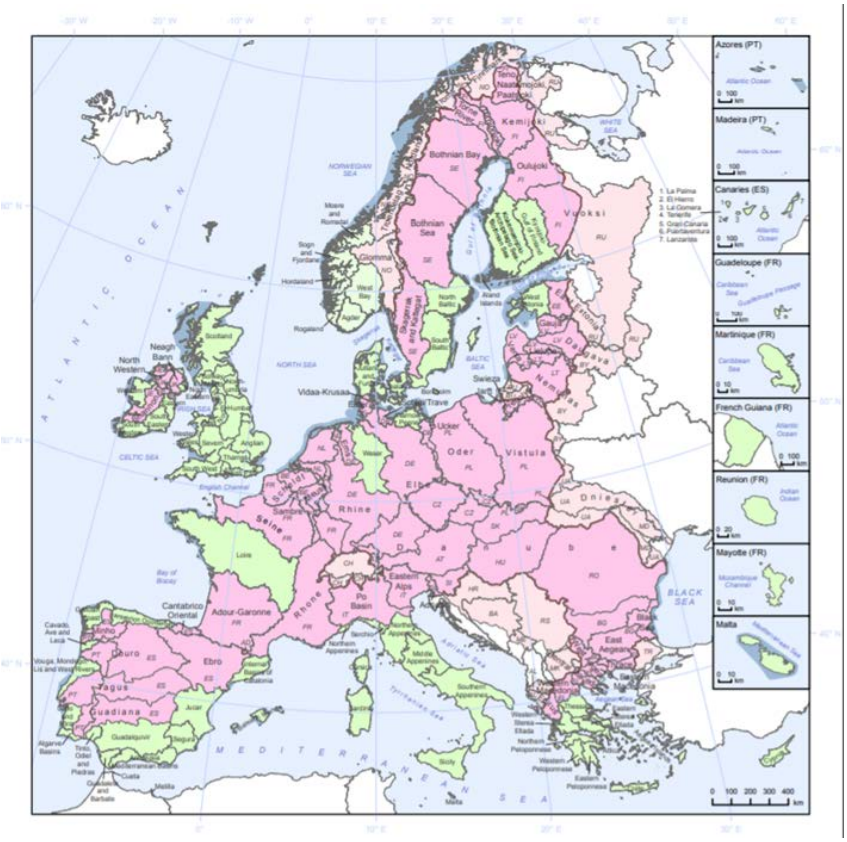
Source: EEA, author's computations.

Following the implementation of the EU Water Framework Directive in October 2000[25], the geographical information of the flood events are organized around the so-called "river basin districts" (RBDs), in that European regions are grouped around their main river basins rather than along their administrative boundaries (Figure A.2).

This particular reporting framework makes the data incompatible with the information we have on the location of European LSIs, which is instead classified according to the NUTS system. In particular, the main difficulty is given by the fact that RBDs can encompass more than one NUTS region. We have nonetheless managed to identify all the NUTS regions corresponding to each RBD by cross-checking our data with the information provided by the European Pollutant Release and Transfer Register (E-PRTR), a Europe-wide database maintained by the EEA that establishes a direct correspondence between NUTS codes and RBDs. While for some of the flood events the original EEA database provides precise information on the affected areas, for other episodes indications are less clear-cut. Therefore, for the former it is possible to establish

[25] See https://ec.europa.eu/environment/water/water-framework/index_en.html.

Figure A.2: European River Basin Districts



Source: EEA and European Commission.

a univocal NUTS-RBD pairing, whereas for the latter codes have been matched assuming an even distribution of events across the NUTS regions corresponding to the single RBDs. Such an assumption would not bias the main findings of the analysis, as this approximation has been applied to a limited amount of events. Moreover, replicating the analysis by excluding these few controversial cases from the sample is not leading to substantially different findings. On top of these integrations, additional location information on some floods not directly detailed in the original dataset has been complemented by means of web searches. Furthermore, the database classifies flood events by duration in number of days as well as severity, the latter being broken down in three main categories: i) “moderate”; ii) “high”; iii) “very high”, with increasing level of intensity.

B Selection of LSIs with a territorial focus

This analysis considers only LSIs with strong interdependence with the territory where they operate and are headquartered. In order to identify these banks, the following algorithm has been adopted. First, all LSIs belonging to the savings and cooperative sectors have been taken into consideration, in that these institutions typically follow a territorial principle, whereby they can only lend to counterparts within a specific geographical area[26]. Furthermore, the sample also includes some LSIs that might still have a clear link to the territory where they operate, although not being savings or cooperative institutions. These institutions are the former saving banks in Italy ("Casse di Risparmio") and the municipal banks in France ("Caisses de Credit Municipal"). Finally, only banks reporting at the highest level of consolidation are taken into account.

These selection criteria narrow the number of sampled institutions down to 1,718 LSIs as of 2019Q4. Most of these banks are located in Germany (1210) and Austria (378) and account for around 64% of the overall LSI sector assets (Table B.1).

Table B.1: Territorial LSIs by country

Country	#	Share of domestic assets	Share of SSM assets
DE	1210	84.11%	53.04%
AT	378	55.35%	4.36%
IT	68	34.84%	2.77%
ES	39	65.90%	2.66%
FR	10	0.25%	0.01%
PT	6	34.26%	0.49%
LT	3	19.38%	0.02%
BE	2	51.22%	0.59%
LU	2	7.41%	0.23%
Total	**1718**		**64.16%**

Source: FINREP, author's computations.
Notes: Data refer to 2019Q4. # refers to the number of banks included in the sample of territorial LSIs.

While the German banks are prominent both domestically and at the SSM level in terms of total assets, however territorial LSIs in Spain, Austria, Belgium, Italy and Portugal hold a substantial share of domestic assets, ranging from 34% (Portugal) to 66% (Spain). Consequently, the potential exposure of these banks to physical risks might have relevant repercussions on the LSI sector's performance in each of these countries.

[26]The selection is based on the sectoral classification reported by NCAs in the 2020 Institution Specific Templates (IST) exercise.

C Regression framework

C.1 Data

Table C.2 reports the list of variables with sources and time coverage.

Table C.2: Data sources and coverage

Variable	Source	Coverage
Macro-financial		
3-month OIS rate	Datastream	2018Q1-2019Q4
Government bond yields (2 and 10 year)	Datastream	2018Q1-2019Q4
VIX	Haver Analytics	2018Q1-2019Q4
Real GDP	MNA	2018Q1-2019Q4
Consumer Price Index	ECB	2018Q1-2019Q4
Banking sector		
Loans to domestic counterparts excluding MFIs	BSI	2018Q1-2019Q4
Herfindahl Index for total assets	SSI	2018Q1-2019Q4
Bank-specific		
Core loans	SUP	2018Q1-2019Q4
Return on Assets	SUP	2018Q1-2019Q4
NPL ratio	SUP	2018Q1-2019Q4
Cost-to-income ratio	SUP	2018Q1-2019Q4
TIER1 capital ratio	SUP	2018Q1-2019Q4
Regional		
Unemployment rate	Eurostat	2018Q1-2019Q4

Notes: MNA: Eurostat National Accounts Main Aggregates; BSI: ECB Balance Sheet Items database; SSI: ECB Structural Statistical Indicators; SUP: ECB Supervisory Statistics.

The variables listed above are included in Equations (1) and (2) transformed as follows: i) the VIX is in log-levels; ii) the real GDP and CPI are expressed as y-o-y growth rates; iii) the denominators of ROA and cost-to-income ratios are seasonally adjusted using the STL decomposition of Cleveland et al. (1990).

C.2 Robustness checks

C.2.1 A more direct approach

In this section, we modify Equations (1) and (2) by including the (log) total number of floods over the period 2000-2014 in each region among the set of regressors[27]. Results, reported in

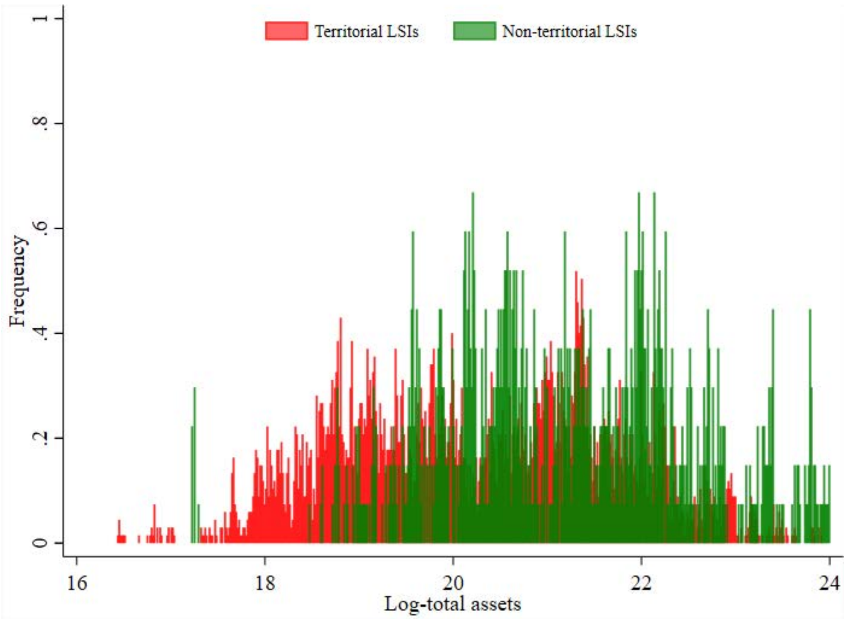
[27] Our approach is based on Murfin and Spiegel (2020), who assess the effect of rising sea levels onto housing prices.

Table C.3, show that the coefficient on the number of floods is generally not significant, but the estimate for core loans gets substantially higher at banks located in riskier areas (+0.037 at 5% significance level, i.e. more than three times higher compared to the baseline estimate). This evidence then provides further support to the baseline setup as well as the findings discussed in Section 3.2.

C.2.2 Sources of banks' heterogeneity

Banks' size might be an important element of heterogeneity when it comes to assess the transmission of risks to performance. Though territorial LSIs are usually smaller local banks (Figure C.3), it is worth investigating whether the sensitivity of these institutions to flood risks significantly changes with size. With this objective we rerun Equations (1) and (2) by disentangling between banks whose size is below the sample median (EUR 810 million assets) and banks above that threshold. In line with what found for the baseline model, results highlight the

Figure C.3: Distribution of total assets at LSIs



Source: ECB supervisory statistics, author's computations.

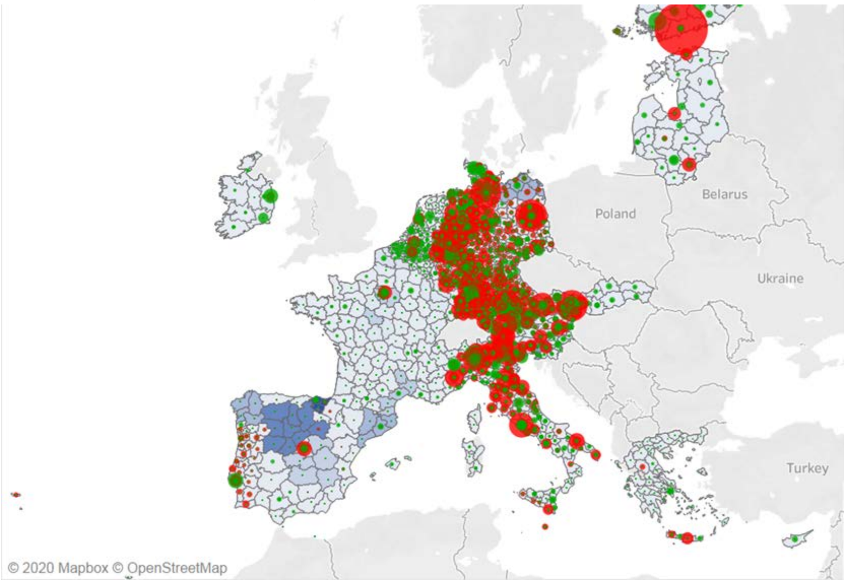
significance of the core lending channel in riskier areas regardless of the banks' size. However, coefficient estimates also seem to suggest that such channel is much stronger at smaller LSIs, independently of whether they are located in less or more risky areas (Table C.4)[28].

Additional sources of heterogeneity can be given by the geographical scope of banks or the

[28] This result supports the idea that bigger banks might be marginally less exposed to flood risks because of better risk management practices.

profile of borrowers. While precise information along these dimensions are not directly reported by banks in the ITS framework, however the peculiar sample under study in this paper, i.e. territorial LSIs, features a higher degree of homogeneity in terms of both. These banks, indeed, by definition base their businesses on traditional lending activity to the real economy, while being very anchored to the territory. It is then reasonable to assume that most of their exposures are towards local and rather homogeneous households and firms, also given that only 13 LSIs in the overall sample (accounting for *less than 5% of total assets* in 2019Q4) have cross-border branches and none of them are classified as territorial. The geographical concentration of the activity of territorial LSIs is also confirmed by some preliminary analyses that have explored the use of more granular databases, like Anacredit (see Figure C.4).

Figure C.4: Loans at territorial LSIs by location of borrowers



Notes: Bubbles dimension is proportionate to the outstanding amounts of loans at each LSI. Red bubbles represent loans towards counterparts residing in the same area as the bank's headquarter, whereas green bubbles correspond to exposures towards extra-territorial borrowers. The shade of geographical units denote the frequency of floods. Darker areas correspond to regions more exposed to severe flooding.
Source: Anacredit, author's computations.

It might be then argued that credit risk is endogenous to the location of both borrowers and banks. In light of the strong geographical concentration of European LSIs, it is possible to account for these non-observed factors by expanding the baseline framework to include region-specific characteristics. Notably, regressors now encompass also the (lagged) unemployment rate at the regional level. Results are reported in Table C.5 and confirm what already discussed in Section 3.2: the core lending channel is significantly stronger at LSIs located in areas more exposed to severe floods.

Table C.3: "Direct approach" regressions for territorial LSIs

Dep. Variable = ROA_t	All LSIs	Territorial LSIs All	Territorial LSIs Lower risk	Territorial LSIs Higher risk
Regressors				
ROA_{t-1}	0.528***	0.422***	0.438***	0.438***
	(0.0600)	(0.0384)	(0.0373)	(0.0373)
Short-term $rate_{t-1}$	0.570	-0.366	-0.0786	-2.344
	(0.451)	(0.330)	(0.362)	(1.847)
Yield curve $slope_{t-1}$	-0.00114***	-0.000103	-5.22e-05	-0.000
	(0.000247)	(0.000286)	(0.000372)	(0.001)
VIX $_{t-1}$	-0.235***	-0.199***	-0.174***	-0.406***
	(0.0162)	(0.0198)	(0.0224)	(0.082)
Equity price $growth_{t-1}$	0.00645***	0.00634***	0.00743***	-0.000
	(0.000644)	(0.000522)	(0.000611)	(0.004)
Real GDP $growth_{t-1}$	0.0563***	0.0457***	0.0435***	0.135
	(0.00832)	(0.00824)	(0.00928)	(0.084)
$Inflation_{t-1}$	-0.0315***	-0.0631***	-0.0692***	0.021
	(0.00764)	(0.0151)	(0.0172)	(0.062)
$Credit/GDP_{t-1}$	0.00398	0.00695	0.00837	0.057
	(0.00582)	(0.00873)	(0.0110)	(0.057)
Herfindhal Index $_{t-1}$	-3.823***	-0.595	-1.962	-7.062
	(1.439)	(4.601)	(4.724)	(5.914)
Total $assets_{t-1}$	0.0401	-0.00235	-0.0110	0.105
	(0.0481)	(0.0289)	(0.0287)	(0.161)
Core $loans_{t-1}$	**0.00856***	**0.00728****	**0.00647****	**0.037****
	(0.00482)	**(0.00363)**	**(0.00300)**	**(0.018)**
Cost-to-income $ratio_{t-1}$	-0.00150**	-0.00183***	-0.00206***	-0.008
	(0.000640)	(0.000663)	(0.000736)	(0.008)
NPL $ratio_{t-1}$	0.000827	-0.00560	-0.0165	-0.028
	(0.00824)	(0.00938)	(0.0109)	(0.069)
TIER1 $ratio_{t-1}$	0.00299	0.00498	0.00251	0.029
	(0.00670)	(0.00866)	(0.00508)	(0.021)
Total floods (log)	0.00347	0.00632	-0.00645	-0.342
	(0.0101)	(0.00450)	(0.00726)	(0.392)
Constant	-0.773	0.0913	0.429	-3.050
	(1.346)	(0.617)	(0.665)	(5.719)
Observations	2,744	2,363	2,363	2,363
Number of banks	507	436	436	436
Bank FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	No
Time FE	No	No	No	No
R^2	0.364	0.454	0.638	0.163

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates in the last column are computed as the sum of the coefficients on regular regressors plus the coefficients on the interaction terms in Equation (2), while the constant is given by $\hat{\alpha}_i + \hat{\delta}$ from the same Equation. The p-values of AR(1) and AR(2) tests are: i) 0.00 and 0.25 in the regression for the whole sample; ii) 0.00 and 0.13 in the regression for territorial LSIs only; iii) 0.00 and 0.202 in the regression for territorial LSIs at high risk.

Table C.4: Regression estimates by banks' size

Dep. Variable = ROA_t	Territorial LSIs Lower risk		Territorial LSIs Higher risk	
	(1)	(2)	(1)	(2)
Regressors				
ROA_{t-1}	0.440***	0.440***	0.440***	0.440***
	(0.0401)	(0.0401)	(0.0401)	(0.0401)
Short-term $rate_{t-1}$	-0.112	0.257	-3.089*	-1.683
	(0.613)	(0.510)	(1.788)	(1.214)
Yield curve $slope_{t-1}$	0.000	-0.001	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
VIX_{t-1}	-0.106***	-0.230***	-0.363***	-0.308***
	(0.031)	(0.025)	(0.067)	(0.097)
Equity price $growth_{t-1}$	0.009***	0.006***	0.001	0.006***
	(0.001)	(0.001)	(0.003)	(0.002)
Real GDP $growth_{t-1}$	0.039**	0.047***	0.082	0.055
	(0.018)	(0.011)	(0.059)	(0.041)
$Inflation_{t-1}$	-0.080***	-0.053***	-0.038	-0.050**
	(0.023)	(0.017)	(0.035)	(0.020)
$Credit/GDP_{t-1}$	0.021	0.001	0.004	0.035**
	(0.017)	(0.011)	(0.018)	(0.016)
Herfindhal Index $_{t-1}$	-3.010	-3.379	-8.765	-7.452
	(5.266)	(4.334)	(5.773)	(4.824)
Total $assets_{t-1}$	0.008	0.019	0.070	0.001
	(0.056)	(0.035)	(0.056)	(0.033)
Core $loans_{t-1}$	**0.011****	**0.002**	**0.018****	**0.006***
	(0.005)	**(0.004)**	**(0.009)**	**(0.003)**
Cost-to-income $ratio_{t-1}$	-0.001	-0.002	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
NPL $ratio_{t-1}$	-0.072	-0.002	0.001	-0.008
	(0.044)	(0.013)	(0.020)	(0.020)
TIER1 $ratio_{t-1}$	0.005	0.008	0.035**	0.010**
	(0.010)	(0.008)	(0.016)	(0.005)
Constant	-0.864	0.607	-2.716**	-1.246**
	(1.372)	(1.060)	(1.559)	(1.223)
Observations	2,363	2,363	2,363	2,363
Number of banks	436	436	436	436
Bank FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
R^2	0.419	0.419	0.419	0.419

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (1): small banks; (2): big banks. The p-values of AR(1) and AR(2) tests are 0.00 and 0.24.

Table C.5: Regressions with regional unemployment rates

Dep. Variable = ROA_t	All LSIs	Territorial LSIs All	Territorial LSIs Lower risk	Territorial LSIs Higher risk
Regressors				
ROA_{t-1}	0.477***	0.423***	0.439***	0.439***
	(0.0533)	(0.0386)	(0.0377)	(0.0377)
Short-term $rate_{t-1}$	0.262	-0.354	-0.0502	-1.576
	(0.412)	(0.329)	(0.365)	(1.357)
Yield curve $slope_{t-1}$	-0.000995***	-0.000121	-6.92e-05	-0.001
	(0.000225)	(0.000283)	(0.000343)	(0.001)
VIX $_{t-1}$	-0.238***	-0.200***	-0.175***	-0.383***
	(0.0159)	(0.0198)	(0.0207)	(0.059)
Equity price $growth_{t-1}$	0.00660***	0.00634***	0.00742***	-0.000
	(0.000689)	(0.000524)	(0.000599)	(0.003)
Real GDP $growth_{t-1}$	0.0388***	0.0457***	0.0441***	0.074
	(0.00850)	(0.00827)	(0.00854)	(0.054)
$Inflation_{t-1}$	-0.0207***	-0.0629***	-0.0682***	-0.013
	(0.00643)	(0.0150)	(0.0147)	(0.030)
$Credit/GDP_{t-1}$	0.00214	0.00722	0.00823	0.014
	(0.00491)	(0.00875)	(0.00919)	(0.019)
Herfindhal $Index_{t-1}$	-3.306**	-0.808	-1.927	-7.934
	(1.397)	(4.550)	(4.156)	(5.492)
Unemployment $rate_{t-1}$	-0.0126	0.00212	-0.00146	-0.009
	(0.00821)	(0.00576)	(0.00605)	(0.037)
Total $assets_{t-1}$	0.0352	-0.00936	0.00213	-0.021
	(0.0461)	(0.0296)	(0.0297)	(0.049)
Core $loans_{t-1}$	**0.00758***	**0.00749****	**0.00640****	**0.020****
	(0.00446)	**(0.00354)**	**(0.00310)**	**(0.010)**
	(0.00446)	(0.00354)	(0.00310)	(0.010)
Cost-to-income $ratio_{t-1}$	-0.00154**	-0.00181***	-0.00206***	-0.004
	(0.000645)	(0.000671)	(0.000762)	(0.005)
NPL $ratio_{t-1}$	0.00584	-0.00713	-0.0173*	0.023
	(0.00819)	(0.00980)	(0.00997)	(0.026)
TIER1 $ratio_{t-1}$	0.000974	0.00414	0.00268	0.026*
	(0.00509)	(0.00877)	(0.00503)	(0.015)
Constant	0.484	0.144	0.202	1.075*
	(1.169)	(0.733)	(0.705)	(2.881)
Observations	2,793	2,363	2,363	2,363
Number of banks	515	436	436	436
Bank FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
R^2	0.376	0.451	0.467	0.467

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates in the last column are computed as the sum of the coefficients on regular regressors plus the coefficients on the interaction terms in Equation (2), while the constant is given by $\hat{\alpha}_i + \hat{\delta}$ from the same Equation. For the system GMM estimator, the p-values of AR(1) and AR(2) tests are: i) 0.00 and 0.42 in the regression for the whole sample; ii) 0.00 and 0.13 in the regression for territorial LSIs only; iii) 0.00 and 0.15 in the regression for territorial LSIs at high risk.

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