WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Container or Content: from Flood Hazards on Firms' Physical Assets to Credit Risks[1]

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Abstract

This paper estimates the potential flood risks for the banking system in France through the non-financial corporation channel. We show the importance of going granular in assessing physical risk. First, the aggregate economic losses at the establishment level appear much higher than at the headquarter level. Second, the losses associated with transferable assets (machines and equipment) are greater than those related to real estate assets. The deterioration of these two types of assets affects the banking system through different channels. Property damages reduce the owner NFC's assets and increase the Loss Given Default (LGD) associated to the premise, while transferable damages can affect the cash position and leverage of the occupier NFC and thus the probability of default. Bank losses associated with transferable assets (the content) are more severe than those affecting properties (the container). Current insurance schemes in France reduce flood vulnerability not only directly for firms but also limit the amplification of vulnerability through the banking system.

Keywords: Floods, Financial Stability, Non-financial Corporations, Credit Risk, Climate Change

JEL classification: G21, G32, Q54

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NON-TECHNICAL SUMMARY

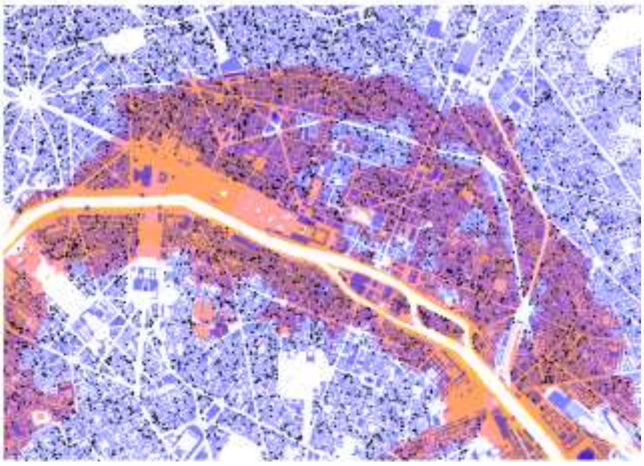
When floods strike, who bears the heaviest losses: the building's *owner*, who sees the property damaged, or its *occupier*, whose equipment and machinery are destroyed? And from the viewpoint of banks, which risk matters most? Put differently: should we worry more about the container (the building) or the content (what's inside)? If the Seine overflows, what will be the spillovers for the banking system? While the frequency and the severity of floods are expected to increase with climate change, will they cascade into to credit risks?

These questions are crucial for monitoring the resilience of the financial system to climate risks and require central banks to combine and analyse very granular data. To that end, our research develops a Digital Twin of French firms. This virtual model closely represents the spatial distribution of French firms' assets and simulates their vulnerability to potential floods. We simulate potential losses under different flood severity scenarios, that we reconcile with historical records.

The paper shows that distinguishing between the building itself and the equipment within is essential for assessing the impact of floods on firms' balance sheets and the banking system. Specifically, we demonstrate that a significant portion of climate-related physical risk resides in geographically dispersed production premises, containing the equipment and machinery and which may be far more vulnerable. While real estate can be repaired or rebuilt, production assets—machines, tools, computers—are often more fragile and more costly when destroyed. These "content" losses are typically larger than those linked to property damage, and because ownership of the building and its equipment often differs, the risks propagate along two separate channels. We find that banks face higher credit risk from the **occupiers' channel** (businesses losing equipment and defaulting) than from the **owners' channel** (landlords facing property devaluation).
At present, France's insurance system contains much of this risk for banks. But our projections show that as climate change intensifies floods, losses will rise sharply, straining the insurance scheme and creating new vulnerabilities for the financial system.

Beyond diagnosis, this work provides a tool for action. The Digital Twin tool can underpin climate-adjusted stress tests, helping supervisors spot fragile loan portfolios and design more targeted safeguards. In particular, it could guide, if needed, the calibration of bank capital requirements, whether at the level of individual institutions or the system as a whole. Finally, by simulating future floods under climate change, the model quantifies the costs of inaction — "no transition" and "no adaptation" — that could be compared to the costs of investing now in transition or resilience. This allows policymakers to weigh trade-off, with a fine identification of winners and losers at the sector/firm level.

Figure 1. Potential floods, buildings and establishments



Note: Each colour corresponds to a return period (probability of annual occurrence) of flooding: yellow for 10 years, orange for 100 years, red for 1,000 years. Black dots represent firms' establishments. Source: Géorisques, Sirene, BNDB.

Le contenant ou le contenu : Propagation des inondations aux risques bancaires via les actifs des entreprises

RÉSUMÉ

Cet article estime les risques potentiels d'inondation pour le système bancaire en France via le canal des sociétés non financières. Nous montrons l'importance d'une approche granulaire dans l'évaluation du risque physique. Premièrement, les pertes économiques agrégées en tenant compte de l'ensemble des établissements apparaissent bien plus élevées qu'en se limitant aux sièges sociaux. Deuxièmement, les pertes liées aux actifs mobiliers (machines et équipements) sont plus importantes que celles relatives aux actifs immobiliers. La détérioration de ces deux types d'actifs affecte le système bancaire par des canaux différents. Les dommages immobiliers sont subis par les entreprises propriétaires et augmentent la perte en cas de défaut (LGD) associée au bien, tandis que les dommages sur les actifs mobiliers peuvent dégrader la trésorerie et l'endettement de la société occupante, et donc sa probabilité de défaut. Les pertes bancaires associées aux actifs mobiliers (le contenu) sont donc plus sévères que celles touchant les biens immobiliers (le contenant). Dans les conditions climatiques actuelles, le régime assurantiel actuel réduit la vulnérabilité aux inondations non seulement directement pour les entreprises mais limitent aussi l'amplification de cette vulnérabilité via le système bancaire.

Mots-clés : inondations, stabilité financière, sociétés non-financières, risque de crédit, changement climatique.

1 Introduction

Physical assets are increasingly exposed to acute climate-related risks, such as floods and wildfires. This vulnerability comes from two converging trends: the increase in frequency and intensity of natural hazards due to climate change (IPCC, 2014) and the continued expansion of human activities into high-risk areas. In Europe, river flooding has historically been a primary source of physical risk, and climate projections indicate this threat will only intensify in the coming decades (IPCC, 2021). In the near future, floods could thus have significant economic consequences for Non-Financial Corporations (NFCs) and the banks that finance them. While implications of climate change are increasingly well-documented at the macro level, a critical gap remains in precisely understanding the channels through which these physical risks translate into financial vulnerabilities and banking risks.

In this paper, we show that distinguishing between a firm's real estate assets (the "container") and its transferable assets, such as equipment and machinery (the "content"), is crucial to assessing the impact of floods on corporate balance sheets and the banking system. Specifically, we demonstrate that a significant portion of climate-related physical risk resides in geographically dispersed production premises, containing the equipment and machinery and which may be far more vulnerable. Crucially, the ownership of the real estate and the equipment within it can also differ. Highlighting these two transmission channels of floods to banking risks, we find that the credit risk related to the occupiers/transferable channel should be more affected than the credit risk associated with the owners/property channel. However, given the current French insurance scheme, potential losses for the banking sector remain contained. We nonetheless show that losses are expected to dramatically increase in the next years, challenging the sustainability of the current insurance scheme.

Compared to previous literature documented by Acharya et al. (2023), we provide a more accurate and nuanced understanding of the potential economic consequences of climate change for French NFCs and the broader financial system by explicitly modelling the differential vulnerability of asset types and their geographic distribution. Our work is close to the European Central Bank (2023) stress-test that evaluates the impact of climate change-induced natural hazards like floods on financial institutions' loan portfolios, using geospatial data, financial information, and risk mitigation strategies like collateral and insurance. Their study, due to European comparability issues, relies on flood data at the NUTS 3 level and firms' geolocation is represented only by their headquarters. Focusing on data at a national level, we complement their analysis by localising the flood risk exposure at the production premise level. We also further analyse the mechanisms through which firms could be impacted by flooding: Did it result in a loss of productive assets, leading to decreased revenues? Did property value decline, affecting the equity available as collateral for credit? These channels are not separately identified, though they likely have distinct consequences, particularly in transmitting economic impacts to the financial system. Working at a national level enables us to rely on very granular data and to distinguish between channels of asset destruction. For instance, our data on buildings displays the economic owner of the building, which we leverage to draft a property damage transmission channel of floods. For hazards data, we use the French official flood maps, which provide higher accuracy than modelled maps often used in cross-country analysis (Dottori et al. (2021)). The latter are available at 100 m resolution and do not account for the influence of local flood defences, in particular dyke system. In our official national map for France, the accuracy of the mapped information is approximately

1:25,000, and the protection from systems such as dykes is integrated.[1] As Fatica et al. (2023) has shown that protective measures significantly reduce the negative flood impact for firms, our official flood data should lead to more realistic results than modelled flood data.

In fact, the literature on the economic consequences of natural catastrophes is expanding and is, in particular, almost flooded by flood-related events.[2] It can be broadly categorised into two main approaches: historical assessments and simulations. Each methodology offers unique insights and complements the other. Historical assessments provide empirical evidence and causal relationships, while simulation-based studies offer the ability to explore a wider range of scenarios, including potential future events under climate change. The former captures behavioural responses, while the latter allows for more controlled experiments and the testing of policy interventions.

Historical assessments use data from single or multiple flood events to evaluate their impact on observable economic variables. These studies employ reduced-form estimates, incorporating behavioural responses to capture macro-level effects (as in Pankratz et al. (2023)). A significant thread within this literature focuses on the (direct and second-round) effect of flood hazards on asset prices, particularly in real estate markets[3]. For instance, Fisher and Rutledge (2021) demonstrates the short-term effects of major hurricanes on commercial property valuations, noting heterogeneous recovery rates across different building types. Another strand examines the link between asset losses and company performance, with mixed findings. Noth and Rehbein (2019) observed improved economic and financial performance for firms in flood-affected regions of Germany following a major 2013 flood, suggesting a potential "creative destruction" effect. However, Fatica et al. (2022) argues that this result may be driven by capital reallocation to non-affected firms within the affected regions. When using the appropriate granularity, the negative effects of flooding on firm performance may appear more significant and persistent. The last strand of this literature studies the impact of hazards on the relationship of affected entities to credit. Holtermans et al. (2022) shows that hurricanes Harvey and Sandy significantly impacted commercial mortgage delinquency rates, while flood insurance mitigated some effects (Sweeney et al., 2022).

In parallel, simulation and model-based analyses form a substantial part of the literature, evaluating potential direct physical damage caused by floods and performing scenario-based assessments. These studies allow for greater flexibility in testing different scenarios and transmission channels. Dottori et al. (2023) provides an example of this approach, assessing the impact of floods on buildings, infrastructure, and population exposure and evaluating the effects of various adaptation strategies (dykes, detention areas, flood-proofing of buildings, relocation). Their work allows for a controlled examination of different mitigation measures and their effectiveness in reducing flood-related damages. Mongelli et al. (2023) employs a stochastic dynamic economic model to project monetary impacts on physical assets, including buildings and agricultural production. This type of modelling enables researchers to explore a range of potential outcomes under different climate scenarios and economic conditions. In a similar vein, Caloia et al. (2023) and Lepore and Fernando (2023) focus on severe and unlikely flood events in the context of financial stress testing. Their study utilises model-based simulations to assess the potential impacts of extreme floods on financial institutions and finds high

[1] Official maps for England, Spain and Po Bassin are 5 m resolution.

[2] Both this focus and ours on floods can be explained by (i) the materiality of the risk, (ii) the availability of data at a granular level, and (iii) the existence of tailored and detailed damage functions.

[3] A whole section of Contat et al. (2024) reviews empirical studies assessing the impact of floods on prices

potential impacts on LGDs and PDs. Similar to their results, we show that the impact through the mortgage market is contained, but, in contrast, that the impact through the occupation and use of machines and equipment could multiply the impact on the banking system significantly.

This paper contributes to reconciling the results from the historical assessment with the stress tests approach. We leverage the flexibility of simulation-based approaches to offer three main improvements, both conceptual and data-driven: i) the definition of physical assets: distinguishing between *transferable* and *real estate* assets enables one to identify the channels through which firms are impacted when a building is affected. Damages to transferable assets represent a loss for the firm that *uses* the building, while real estate damages negatively impact the firm that *owns* the building. As far as we know, this is the first time that this distinction has been made to analyse and assess physical risks to firms. We show in section 4 that this distinction is empirically relevant. By incorporating the moderating effect of insurance into our analysis, we simulate a 1% average impact of floods on firms' total assets. This adjustment aligns our model with observed outcomes: we then demonstrate that this result is consistent with the historical effects on the balance sheets of firms located in flooded areas. Our framework thus not only reflects empirical evidence but also enables forward-looking simulations, offering a robust tool for anticipating future financial vulnerabilities. ii) A clear identification of transmission mechanisms of climate hazards to the banks exposed to impacted firms. Real estate damages reduce the owner's equity and the LGD associated with the premise, while damages on tangible assets can affect the income of the user and, thus, its repayment capacity and PD. iii) The reliance on very granular datasets, both for geographical data (climate hazards, physical assets should be geolocated at a very fine level) and economic/financial data (firms' balance sheets and loans).

To do so, we develop and use a Digital Twin tool, the outcome of an international project led by Banque de France (BDF), De Nederlandsche Bank (DNB), and the Hong Kong Monetary Authority (HKMA) (de L'Estoile et al., 2025). Their goal was to develop a common and flexible tool for supervisory authorities, based on the adaptation of the concept of Digital Twins. These virtual models of physical objects, like buildings, are used to simulate shocks such as climate-related hazards (Sharma et al., 2022). Their use is widespread in engineering and industrial sciences, and increasing for modelling urban systems (Dembski et al., 2020). An important innovation of this paper is the development of an urban Digital Twin that can be connected to a financial system extension.

While section 2 and 3 detail the data and methodology we rely on, section 4 empirically assesses the fit of our framework, while Section 5 details our results. Section 6 uses our setup to estimate future losses according to climate change and insurance gap scenarios, and, finally, section 7 concludes.

2 Data

This paper uses three public databases for geographical information about buildings and floods, and two databases provided by the Banque de France and the French banking supervisor (ACPR) for non-financial corporations' balance-sheet level and loan-level data.

2.1 Data on buildings

The BNDB (Base de Données Nationale des Bâtiments, National Buildings Database) is a mapping of the existing building stock in France. Structured at the "building" level, it provides detailed information for each of the 20 million residential or tertiary buildings in France. It is built by the CSTB using a geospatial intersection of around twenty public organisations' databases. While CSTB develops different products, we use the open dataset. Among many, the variables we use are the location of the building, the group of buildings to which it belongs and the owner.

2.2 Data on flood hazards

The information on flood hazards we use is static maps of flood-prone areas with high human, social, and economic stakes, the *Territoires à Risque d'Inondation (TRI)*. It is constituted of polygons, each of which is characterised by a certain level of risk (high, medium and low probability of occurrence corresponding to *circa* 10, 100 and 1000 years return periods) and a water height level. The fact that TRI focuses not on all hazards but only on those with significant exposure should not be of concern to us, as we do not try to explain the location of firms. Flood scenarios are:

- High return period: An event causing the first significant damage, with a return period between 10 and 30 years.
- Medium return period: An event with a return period between 100 and 300 years. If a historical reference event is not used, a centennial-type event is sought.
- Low return period: An exceptional flooding event inundating the entire area of the functional alluvial plain (major bed) or the functional coastal plain, and for which any protection systems in place are no longer effective. As an indication, a return period of at least 1000 years is sought.

2.3 Data on localisation of past floods

We use CatNat data on postal codes affected by floods, as defined by the French CatNat insurance system for natural disasters. Under this system, private insurers include natural disaster coverage in standard automotive and property policies. When a disaster occurs, a committee determines if it qualifies as a natural disaster. If so, the affected municipality receives the CatNat designation, and insurers compensate the victims. Additionally, firms may receive subsidies to cover disaster costs.

2.4 Data on firms and establishments

All French firms are characterised by a SIREN identifier. Establishments are firms' producing premises, which are located in buildings. Produced by Insee, the Sirene dataset (Répertoire National d'identification des entreprises et des établissements) provides information on each business establishment located in France. We obtain the geolocation of each establishment by merging this dataset with the "Géolocalisation des établissements du répertoire Sirene" dataset,[4] based on the SIRET identifier. We also use FIBEN data to get details on firms' balance sheets. Since 1989, FIBEN has gathered balance sheet data based on fiscal declarations at the unconsolidated level on all companies whose turnover exceeds 750,000 euros.

[4] https://www.data.gouv.fr/fr/datasets/geolocalisation-des-etablissements-du-repertoire-sirene-pour-les-etudes-statistiques/

2.5 Data on loans

AnaCredit is a dataset from the European Central Bank that contains detailed information on individual bank loans in the euro area, with collection starting in 2018. Loans are reported if their amount is higher than 25,000 euros at the bank-firm relationship level. In this dataset, we use the one-year probability of default of the counterparty (PD) evaluated by the bank as prescribed by the Capital Requirements Directive. Only banks reporting in the internal rating (IRB) report the PD in AnaCredit and can use them in the computation of capital requirements. According to the EBA guidelines, the PD should include expert judgment and "cannot be a purely statistical process, but to some extent also has to involve human judgement, to make sure that the models are appropriate for current and foreseeable portfolios and conditions, and that the models are acceptable for business users" (European Central Bank, 2017). Table 4 shows descriptive statistics for NFCs' loans from Anacredit.

3 Methodology

3.1 Conceptual framework and data matching

Our first contribution is to develop a Digital Twin model to measure the impact of flood risk on credit risk by distinguishing real estate properties from transferable assets that lie inside them[5]. This distinction matters for several reasons. It is in line with the analytical framework used by the national experts on flood damages: the National Research Institute for Agriculture, Food and the Environment in France, INRAE, explicitly developed property and transferable damage functions associated with flooding (Bremond et al. (2024), see more below). We define i) *property* damage as a drop in the value of the affected building or the necessity to pay repair costs, and ii) *transferable* damage as the destruction of physical assets inside the building (machines, physical capital). While indirect damages, such as the flooding of infrastructure or the breakdown of value chains (with customers or suppliers affected by floods), may be even higher than these direct damages, they are very difficult to grasp. As we do not have access to the damage functions for these indirect costs, we decided not to take them into account.

The entities affected by these two types of damage differ most of the time: while commercial real estate has increasingly become a financial asset, the user of a premise in a building is not necessarily the owner of this premise. In these cases, there are many transferable and real estate assets that do not belong to the same entity. Table 1 recapitulates how losses are distributed between the firms that are connected to a building when it is flooded.

Table 1: Damage and firm types

Firm Type	Owner	Occupier	Owner-Occupier
Property damage	Yes	No	Yes
Transferable damage	No	Yes	Yes

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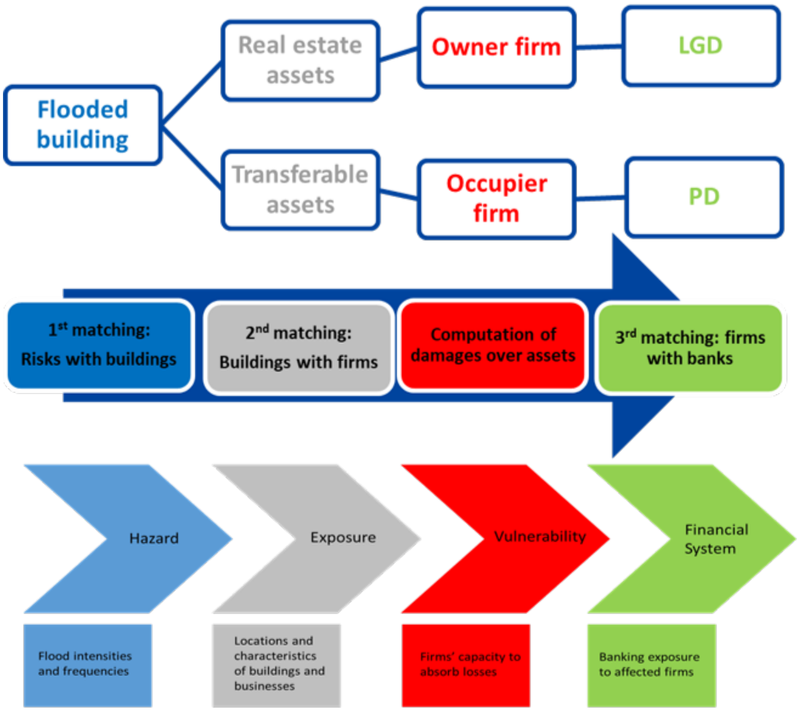
[5] The tool is based on a bottom-up approach, enabling the adaptation of the inputs in a very flexible manner. As described in de L'Estoile et al. (2025), others have used this tool to assess the impact of flood risk in the Netherlands or typhoons in Hong Kong.

When a building is flooded, its owner will face property damages, reducing its asset value, while transferable damages are the cost for the occupier. Firms occupying the building they own (or when the user and owner firms belong to the same entity) face both property and transferable damages[6].

Figure 1: Sketching summary



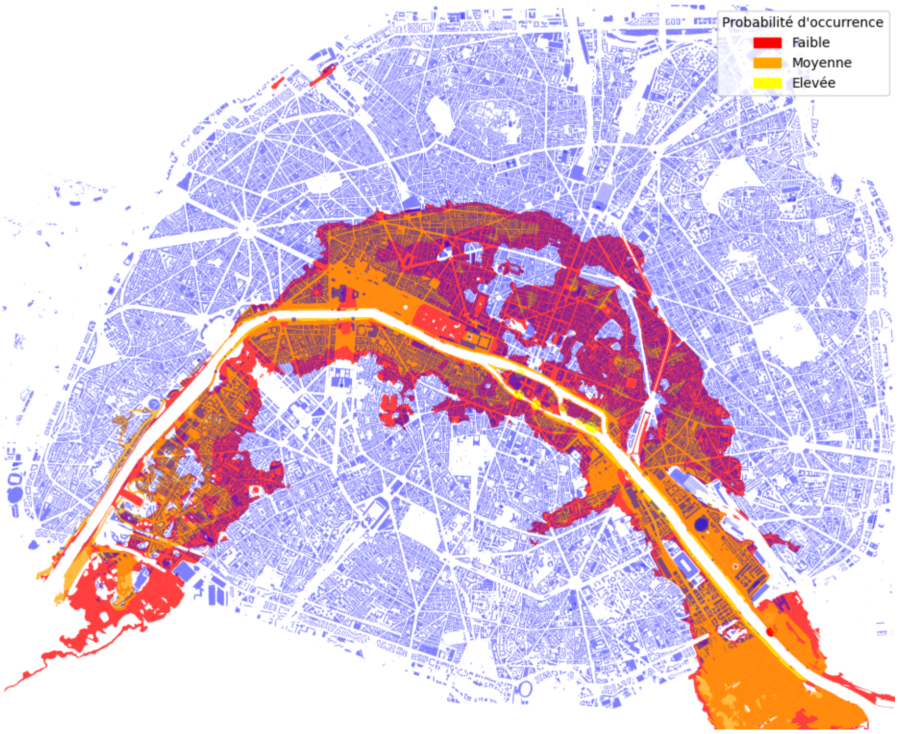
Note: Floods transmit to banking risks through two channels: real estate damages that lead to an increase in Loss Given Defaults (LGDs) and transferable damages that tend to increase the Probability of Default(PDs).

Figure 1 summarises this analytical methodological framework that is embedded in the hazard-exposure-vulnerability-finance structure. The decision tree derives the transmission from climate hazards to credit risk metrics, while the successive methodological steps lie at the bottom. One major point of the methodology is the reliance on an intermediary object between hazards and firms: the building. Whereas direct matching could seem more straightforward at first sight, this method is likely to imply important errors. In effect, the geolocation of establishments is represented as a point and thus does not account for their real physical exposure. The building step enables to give establishments back their real land footprint.

Our model first localises buildings exposed to flood **hazards** at a very high resolution (5 meters). For each building that has been spotted as **exposed** to floods, we identify its owner(s) and user(s). This step corresponds to the buildings with firms matching (one distinctive matching for owners and one for occupiers). For that, it computes the spatial intersection between the BNDB and the TRI at the building level, obtaining the flood hazards it is exposed to according to three scenarios (high, medium and low occurrence probability) for each French activity building. Figure 2 displays the buildings and the probability of flood occurrence. As a building can lie on several flood hazard polygons, the model is parametrised to keep only the polygon whose overlap area with the building is the largest.

[6]The share of own-users is hard to clearly identify because many firms own real estate through a Sociétés Civiles Immobilières (SCI), a common type of firm in France that is often used by non-real estate firms to manage their real estate assets. Thus, even in the case of own-use, the owner will have a different identifier from the user. However, de l'Estoile (2025) finds that 50% of Commercial Real Estate buyers are own-users.

Figure 2: Hazards and buildings

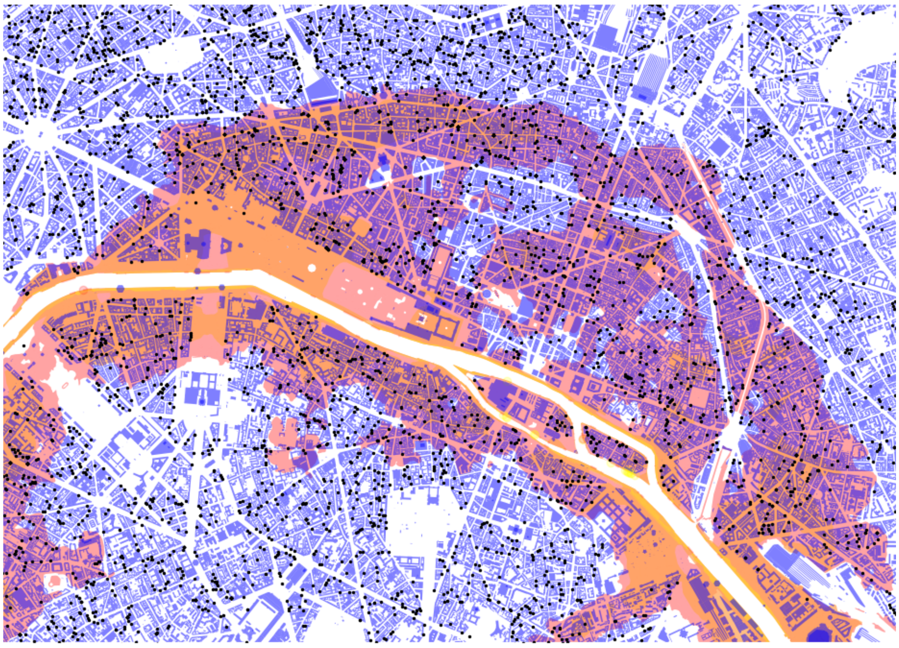


Secondly, we compute for owners and occupiers the associated damages and relate them to firms' balance sheets to assess their financial **vulnerability**. Most of the activity buildings do not belong to the firm that occupies them. French data on CRE transactions show that about half of the volume is bought by investors (de l'Estoile, 2025). Concerning *owners*, BNDB displays information on each building's owner: when it is owned by a legal entity (firms, most of the time), it is associated with a SIREN identifier. This very precious information thus enables us to identify the owners of exposed buildings and also to compute some statistics on them. Concerning *occupiers*, we match together establishments and buildings. Figure 3 depicts this geographical matching in central Paris. We match each black dot representing an establishment (SIRENE database) to the nearest polygon representing an exposed building using a nearest-neighbour spatial joint. While each establishment can only be matched with one building, multiple establishments can be in the same building. In order to increase the relevance of the matching, some filters are applied to the establishments database: only perfectly geolocated establishments are kept, while establishments that self-declare as non-employing are removed from the sample to get rid of individual entrepreneurs, SCIs[7] or virtual office companies, whose physical footprint, and hence exposure, is limited. This method is similar to the one developed and detailed in de L'Estoile and Salin (2024), with a slight difference. While they match establishments with parcels from the Fichiers Fonciers database, we match them with buildings from BNDB.

Finally, we connect the losses to banks and specific **credit risk metrics**. Transferable damages impair the productive capacity and the balance sheet of firms and can thus reduce their repayment capacity and probability of default (PD). Property damages decrease the value of the premises. While a significant share of NFC loans are collateralised by a real estate property, a drop in the value of this

[7]SCIs, or Sociétés Civiles immobilières are a specific type of legal entity in French law used for real estate management and ownership.

Figure 3: Buildings and establishments in Central Paris



property increases the loan LGD, i.e. the value that the lender will not receive in case of default of the creditor.

3.2 Calculation of sector-varying transferable and real estate assets damages

Our calculation of damages follows the methodology of the Ministry for Ecological Transition, Energy, Climate and Risk Prevention in France (Rouchon et al. (2018), Bremond et al. (2024)). The chosen method to build them involved developing theoretical modelling of damage based on expert assessments. It does not rely on statistics based on previous events but on insurance experts' interviews in 2013. When developing flood damage functions for French firms, experts recommended distinguishing between real estate and transferable damages. Our choice for a specific damage function at the asset-sector level is a claim for the bottom-up approach at the core of our Digital Twin model. Indeed, it is richer than other damage curves, such as the ones developed by Huizinga et al. (2017) that have only five categories (residential, commercial and industrial buildings, transport infrastructures and agricultural land) for many countries.

The methodology for constructing the damage functions we use involved the following steps:

- Definition of a typology of businesses
- Creation of damage functions for basic components: expert interviews about the value of different restoration actions for the property based on the water height and the duration of submersion.
- Construction of business models and generation of damage functions for these models using basic damage functions
- Initial validation of these functions with the consulted experts
- Reconstruction of damage coefficients for equipment and inventory for each model

- Development of national damage functions consistent with the sectoral typology

Damage functions depend on the severity of the flood (height) and on the size of the asset loss: the size of the building in m² for property damages and the size of the firm in terms of employees for transferable damages (on equipment). The damage functions vary depending on the sector of the establishment that is affected. The formula to compute direct damages on real estate assets is:

$$\text{Real estate damages}_{a,s} = \text{Size } \theta_{a,s}\pi$$

Where Real estate damages$_{a,s}$ is the damage in € 2022, S the floor area in m2, $\theta_{a,i}$ the damage per m2 with s the intensity of the flood scenario and a the activity of the firm and π is a correction factor to compute damages in terms of the 2022 price level.

Direct damages to economic activities for equipment and stocks are modelled according to the equation:

$$\text{Tangible assets damages}_{a,s} = \text{Size } \theta_{a,s}\pi$$

Where Tangible assets damages$_{a,s}$ where the parameters are defined as above, but Size is the number of employees and $\theta_{a,s}$ the damage per employee.

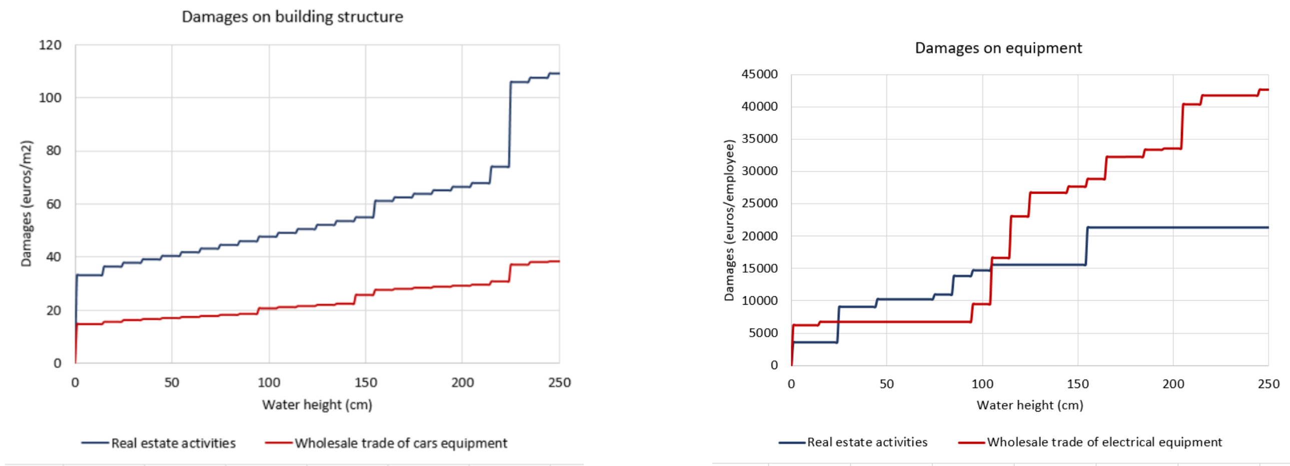
For some economic activities, damage functions were not computed because they are very specific (Aeronautics, Extractive industry, Chemical industry) or because they concern employer households - in that case, they are included in housing damage functions because activities are mobile.

Figure 4 compares the damage functions for establishment in Real Estate activities and Wholesale Trade of Car Equipment. Establishments in the sector of Real Estate activities are mostly located in offices in vertical properties without expensive machinery, while Wholesale Trade buildings are composed of administrative space and logistic warehouse. These warehouses are often made of concrete with no flooring, making them easier to maintain after a flood in comparison to commercial premises with more delicate flooring. Therefore, the cost per m2 of flooding on the building structure is higher for Real Estate activities than for Wholesale Trade of Cars Equipment. Concerning equipment, the cost per employee is close in the two sectors, until a threshold of water height of 25 cm. Indeed, electrical equipment is already sensitive to humidity, but when it is in contact with water, it needs to be fully replaced. This equipment can be stored high, but when the flood reaches a certain level, it is not enough to protect them.

Since the BNDB is at the building level and since the geolocation of the establishments is in two dimensions, our information remains at the building level. Thus, we are not able to directly tell whether the owner or the user of a premises is on a floor directly affected. This is a serious caveat and should, of course, not be neglected. However, the structure of the damage matrix should mitigate this issue. In effect, it gives more weight to industrial or commercial activities than office activities. While the latter is hosted in buildings with multiple floors, industrial or commercial activities tend to be located in 1-floor buildings (see [de L'Estoile and Salin (2024)]). Thus, the sectors that will face important damage should be the ones for which the issue of the floor is less relevant. One useful robustness check would be to divide losses by the number of floors. Unfortunately, the BNDB data does not provide this information.

Finally, business interruption losses are not included in the damage functions because these types

Figure 4: Damage functions - on building structure vs on equipment



of losses are difficult to model from a methodological perspective for three reasons: i) They may correspond to economic transfers at the national scale; ii) They depend on the duration of the operational shutdown of establishments; iii) They may be compensated over time.

3.3 Insurance protection against flood risk for commercial real estate in France

Insurance plays a critical role in mitigating the direct transmission of losses from firms to banks. In light of growing concerns about insurance coverage gaps and the increasing uninsurability of certain properties in specific sectors or regions, we simulate various insurance coverage scenarios. In France, insurance coverage is mandatory for renters and shared spaces in the case of co-ownership arrangements, but not for property owners (outside shared spaces)[8]. Natural disaster coverage is compulsorily included in all property insurance. Banks ask the counterparty to take insurance for a mortgage contract. However, this type of insurance only covers temporary incapacity to work, total and irreversible loss of autonomy, permanent disability and death.

In France, firms will be insured against flood risk if they have already insured their building or goods for fire damage or any other property damage. The minimum amount of money an insurer will not pay toward a covered claim is 10 % of professional goods if the flood is recognised as a natural hazard by an inter-ministerial commission. It could be higher depending on the initial insurance. If the municipality does not have a risk prevention plan, the deductible is doubled for the third decree declaring the disaster, tripled for the fourth, and quadrupled for subsequent decrees. The insurer has 3 months to provide insurance. Insurance penetration is estimated by EIOPA to be between 75 % and 100 %.

We choose to simulate the level and dynamics of aggregate firms' losses depending on the insurance coverage. With an α_t that represents the total share of insured losses, we can define the losses according to the following equations when applying scenarios or projection data in the rest of the paper. We make the hypothesis that for each firm, the same share α_t of damages is covered.

$$D_t = C_t^f + C_t^a \tag{1}$$

[8] https://entreprendre.service-public.fr/vosdroits/F37365

At each period t, the total damages D_t (*Real Estate Damages* + *Tangible assets damages*) are distributed between the costs for firms C_t^f and the costs for insurance C_t^a.

$$C_t^f = \sum D_i, t * (1 - \alpha_i, t) \tag{2}$$

With D_i, t, the individual damages faced by firm i at time t and α_i, t, the share of their losses that are uninsured. Making the assumption that firms are homogeneous, this simplifies to:

$$C_t^f = D_t * (1 - \alpha_t) \tag{3}$$

3.4 Credit risk assessment methodology

3.4.1 Bank credit risk modelling

In the AnaCredit register, the counterparty's probability of default calculated by the bank is available for banks reporting with an internal ratings-based (IRB) approach in the Capital Requirement Regulation (CRR). The underlying model used by each bank is not public; however, it should follow the regulation and the European Banking Authority (EBA) and ECB guidelines (European Central Bank (2017) and European Central Bank (2024)). According to them, the PD estimation must be based on the material drivers of the risk parameters. These include, but are not limited to, climate-related and environmental risk drivers affecting the PD, where relevant and material. The model should include the following potential risk drivers:

- for SMEs: country, industry NACE 1, size in terms of total assets, past delinquency
- for large corporates: industry, country, size in terms of turnover

3.4.2 Projection of probability of default

Given that banks' credit risk models are not public, we estimate a PD model with key risk factors that should be used by central banks (Antunes et al. (2016)) in order to recover the underlying model and the correlation between risks' drivers for the counterparty and the average one-year probability of default estimated by banks. As mentioned in Auria et al. (2021), "a key aspect in the rating process is the analysis of financial ratios, which covers all areas of relevance for analysing financial soundness, i.e. (i) the ability of the enterprise to generate cash from its operations to meet current financial obligations, (ii) the balance between its short-term debt and its liquid assets, (iii) the balance between its total debt and its assets, and (iv) the ability of the enterprise to make profits." In the line of Lee (2024), we shock some variables under different flood scenarios and then project the new probability of default.

First, we start with an econometric analysis to establish correlations between the average PD declared by the bank and risk drivers of the NFC, which could be affected by the impact of flood on assets. As the PD is a continuous variable between 0 and 1, we estimate the sensitivity of firms' balance sheet items with OLS, controlling for firm and time-fixed effects. As explained by Antunes et al. (2016), credit risk models reflect several features such as solvency, profitability and liquidity. For this reason, we include a variable for each component in our model: *Leverage* for solvency, *Profit* for profitability and *Cash ratio* for liquidity.

$$\text{PD}_{i,t} = \beta_1 \text{Leverage}_{i,t} + \beta_2 \text{Profit}_{i,t} + \beta_3 \text{Cash ratio}_{i,t} + \theta_i + \theta_t + \epsilon_{i,t} \tag{4}$$

Where:

- the dependent variable $\text{PD}_{i,t}$ is the average probability of default as calculated by banks for the counterparty i at time t. We estimate the model at a yearly frequency, as firms' annual accounts are updated yearly
- $\text{Leverage}_{i,t}$ is defined as total bank debt/total assets for firm i
- $\text{Profit}_{i,t}$ is defined as EBITDA/total assets as in Lee (2024)
- $\text{Cash ratio}_{i,t}$ is defined as cash/total assets.
- We control for firm fixed effect θ_i and time fixed effects θ_t.

This model is estimated with yearly balance sheet data from 2018 to 2023 (due to the starting date of the AnaCredit reporting). We compute the average probability of default for the firm declared by banks in Anacredit, and we merge it with data on the firm's balance sheet, FIBEN. [9] Table 2 displays the result of our regression. Model 1 shows that a higher leverage corresponds to a higher probability of default and a higher profit to a lower probability of default. As the liquidity level of firms is also important for credit risk, we complement the model with a ratio of cash over total assets. A higher level of cash is correlated with a lower probability of default.

Then, we make some hypotheses about how the damages affect the level of assets. If bank loans to firms are in default, the bank may recover the value of the real estate, devalued by the amount of the damages.

The leverage remains unchanged if no flood occurs. For owners, the leverage increases as total assets are depreciated by the amount of the damage. For occupiers, we consider that they first use their cash to face damages and that their leverage increases if their cash is insufficient.

$$\text{Cash ratio}_{i,s} = (\text{Cash}_i) - \text{Damages}_{i,s}\text{Cash}_i) - \text{Damages}_{i,s}{\scriptstyle \text{Cash}_i) - \text{Damages}_{i,s}{\scriptscriptstyle \text{Cash}_i) - \text{Damages}_{i,s})/}}$$

$$\text{Leverage}_{i,s} = \text{Debt}/(\text{Assets} - \text{Damages}) \tag{6}$$

Then, we can calculate the new probability of default by applying the estimated coefficients $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ to the initial profit, cash ratio value, sectoral probability of default and the new leverage value:

$$\Delta\text{PD}_{i,s} = \beta_1 \Delta\text{Leverage}_{i,s} + \beta_2 \Delta\text{Profit}_{i,s} + \beta_3 \Delta\text{Cash ratio}_{i,s} \tag{7}$$

[9] By matching Fiben and AnaCredit, we lose 50 % of firms as FIBEN mainly contains data about firms with annual turnover higher than 750,000 euros.

3.4.3 Expected losses for banks

We use the projected probability of default (PD), loss given default (LGD) and exposure at default (EAD) to calculate expected losses as:

$$\Delta\text{EL} = \sum_i \Delta\text{PD}_i.\Delta\text{LGD}_i.\text{EAD}_i \tag{8}$$

Loss-given defaults (LGDs) are not reported in AnaCredit. Hence, we approximate loan-level LGDs by looking at the collateral value relative to the notional value of the loan. This is predicated on the assumption that, in the event of a default, a bank can only recover the collateral assigned to the loan and that it will be paid the full collateral value.

$$\text{LGD}^i_S = \max\left(0, \frac{L^i - C^i_S}{L^i}\right) \tag{9}$$

with L_i the outstanding amount of the loan and C^i_S the collateral value of CRE considering the damage specific to scenario S. The collateral value is depreciated by the damage impact estimated by the damage function. We only consider positive values corresponding to cases in which the lender will not be able to recover the exposure in full.

For the owners, we make the hypothesis that the bank recovers the value of the real estate, depreciated by the amount of the damage, in case of firm default. *For the occupiers*, we assume that the value of the collateral is not affected as the occupier does not own the collateral affected by the flood. As LGD and PD tend to be correlated, it is also useful to assess the effect on the probability of default of owners' loans.

If an NFC is at risk of defaulting in the context of a flood, we can discuss two cases:

- The occupier owns other properties not affected by the flood: if the Loan-To-Value (LTV) is higher than one, a share of the loan can still affect the loss given default.
- The occupier does not have any collateral associated with the loan. The damages can directly affect the LGD.

Therefore, the exposure at default only concerns loans with an LTV higher than zero.

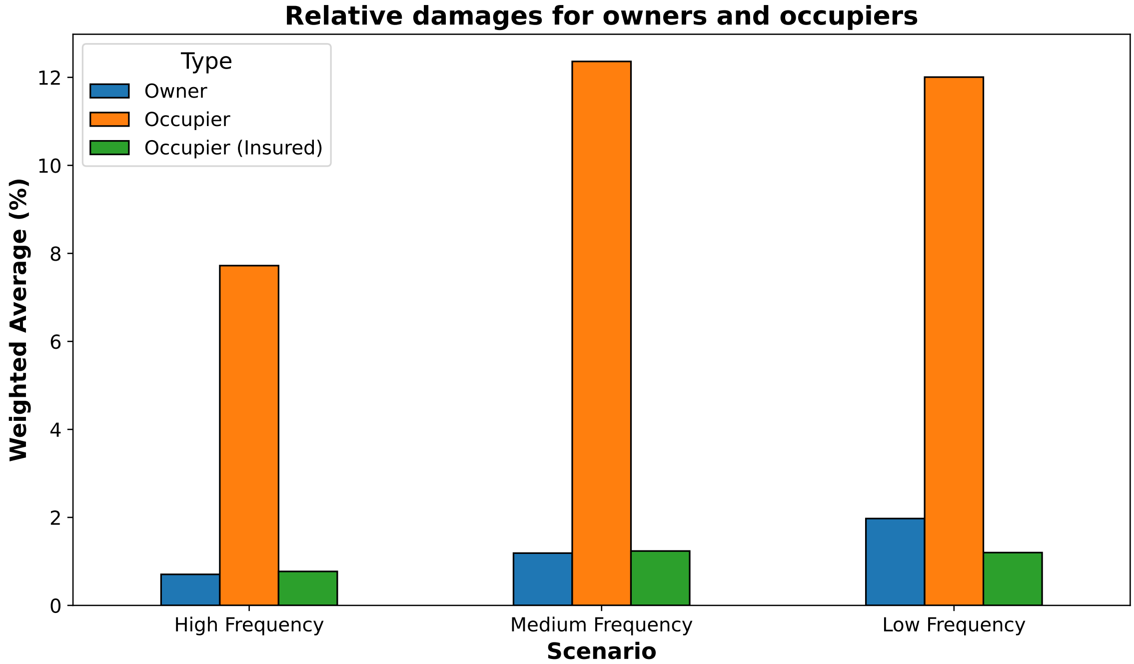
4 Model fit

The aim of this Section is to assess the fit of our simulation framework by comparing our simulated damages with firms' historical asset losses. First, we compute the relative cost of floods estimated by our differentiated damage functions for tangible and real estate assets. Second, we compare them to the estimation of the impact of past floods in France on firms' assets.

4.1 The relative cost of floods for owners and users

Figure 5 shows the average damages projected by our damage functions for users and owners relative to initial assets. We find that average damages for a 1-in-30-year flood are between 1%

Figure 5: Relative simulated damages from national functions



Note: % of real estate assets for owners and % of tangible assets for users. Sample: NFCs exposed to a specific scenario.

4.2 Past flood damage in France

To estimate how firms' outcomes have been affected by past floods and be able to compare it with our simulated results, we use the local projection method (Jordà, 2005). Our regression is inspired by Fatica et al. (2022) and Roth Tran and Wilson (2024), showing that local projections generalise a two-way fixed effect event study. Thus, we run separate regressions for each horizon $h = 0,...,8$ years :

$$\Delta_h y_{i,t+h} = \beta_h F_{i,t} + \sum_{\tau=0,\tau\neq t}^{h} \theta_\tau F_{i\tau} + \sum_{\tau=0,\tau\neq j=0}^{5} \rho \Delta_h y_{i,t-j} + \gamma_h X_{i,k<t-1} + \delta_{d,t} + \delta_s + \epsilon_{i,t+h} \tag{10}$$

Where the dependent variable is the cumulative percentage change in the value of economic outcome $y_{i,t}$ from period t to $t+h$ for firm i (log $(y_{i,t+h}) - log(y_{i,t-1})$. We look at the following outcomes: real estate asset value, technical equipment value, cash value and EBITDA.

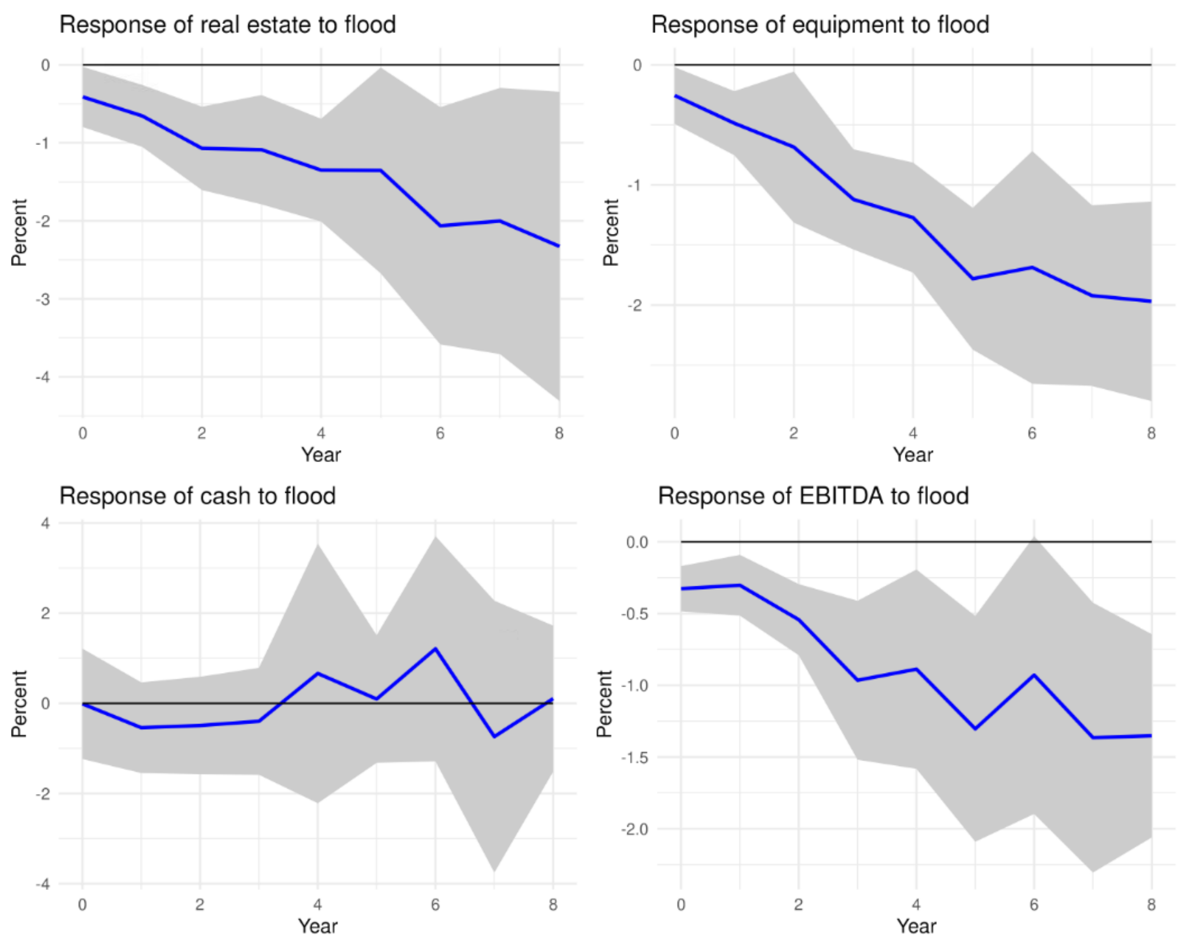
The treatment variable $F_{i,t}$ is a binary variable indicating whether the city where the firm is located has been affected by a flood at time t. The term $\sum_{\tau=0,\tau\neq t}^{h} \theta_\tau F_{i,\tau}$ controls for cumulative effect due to other floods that have hit the same firms before the current one or between the current one and the time h that may have biased the IRF.

With $\sum_{\tau=0,\tau\neq j=0}^{5} \rho\Delta_h y_{i,t-j}$, we control for lags of the dependent variable to eliminate pre-trend and choose a length of 5 lags in line with Montiel Olea and Plagborg-Møller (2021), as in Müller and Verner (2024). To avoid bias in estimated parameters with fixed effects in panel data (Nickell, 1981), Almuzara and Sancibrián (2024) also show that including lags as controls leads to robust inference when assessing micro responses to more macro shocks, as in our framework. The vector of firm-specific variables $X_{i,k<t-1}$ includes the number of employees, the first and second lag of total assets, the share of technical equipment among total assets, the share of real estate among total assets, the share of

liquid assets among total assets, the leverage ratio, the age and the NACE Level 2 sector. We control for sector-level heterogeneity and also include department by year fixed effects to absorb economic shocks in the department in which the city is located that may confound with the flood occurrence. The year fixed effects also control for the macroeconomic environment in France over time, as all the firms have their headquarters in France.

Figure 6 shows a small negative impact of past floods on real estate and equipment, but a more unclear impact on cash ratio or return on assets. These past losses in cities affected by floods appear quantitatively comparable to the estimation from our damage function. Our tangible assets simulated damages are higher than what has been observed in the past. One explanation could be that our simulations assume that the equipment is located on the ground floor, while it could be higher in the building. Also, in the local projections regression, we locate the flood exposure at the city level (because we do not have access to more granular data about historical floods), while in our stress test framework, the flood localisation is much more granular.

Figure 6: Effect on real estate and transferable assets - Main



Note: impulse response to a flood shock. The sample is 1989 - 2023. 90 % significance bands displayed. Mono-establishments only.

Several robustness checks are implemented. To control for spatial autocorrelation, we also apply Conley (1999) standard errors that allow for spatial autocorrelation with a distance threshold of 200 kilometers and serial correlation (Newey-West) up to 5 years, thus controlling for temporal persistence in graph 24 in the Appendix. We also control for sectoral dynamics by replacing the department * time fixed effect by sector * time fixed effect in graph 25 and maintaining a department fixed effect.

To ensure they do not drive the results, we also exclude firms affected by several floods the same year in graph 26. Finally, we also extend the analysis to multi-establishments only and find less significant results. Indeed, location diversification provides resilience against local shocks. However, as multi-establishments represent only 15 % of our sample, the average impact on the full sample remains significant (see Graphs 27 and 28 in Appendix.)

5 From physical exposure to financial risks

Our results are split along the distinction we make between occupiers and owners. We start by displaying potential damages by region and sector. Then, we look at relevant credit risk metrics: Probability of Default for occupiers and Loss Given Default for owners. In this section, we aggregate the damages at the firm level for regional flood scenarios. For instance, an NFC located in Paris with an establishment in Auvergne-Rhône-Alpes will face the sum of the damage of all the establishments in the Auvergne-Rhône-Alpes medium return flood scenario.

5.1 Vulnerability to flood risk: occupiers vs owners

In this section, we evaluate the potential damages before insurance compensation.

5.1.1 Potential damages geographical distribution

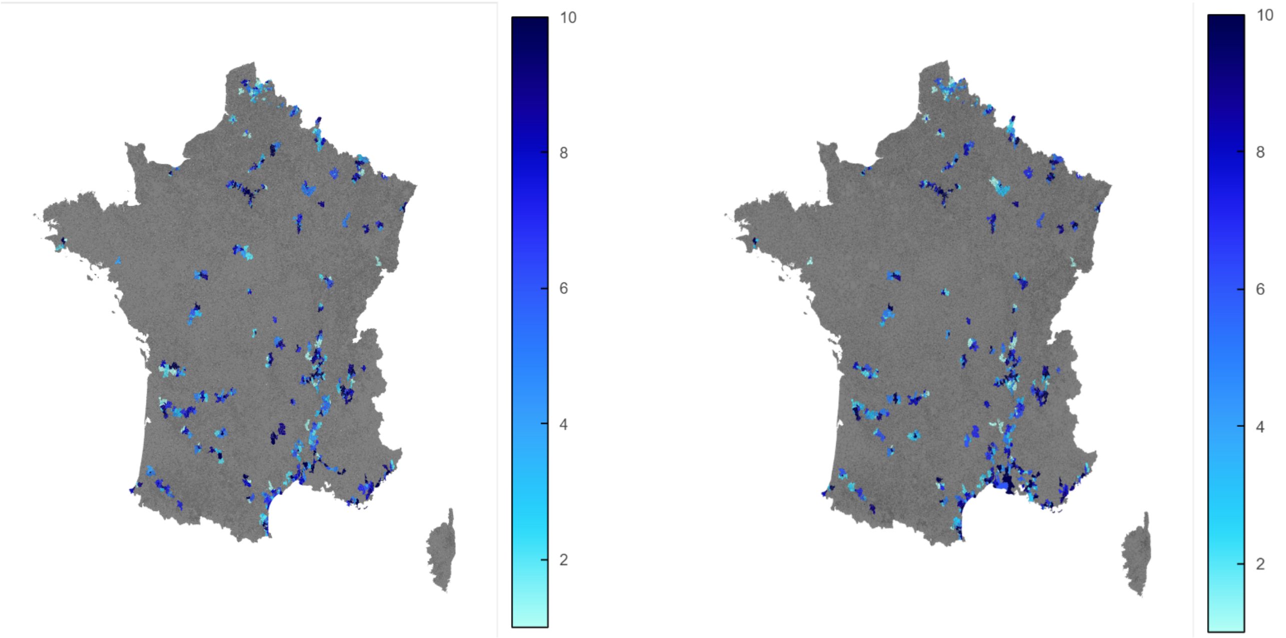
Figure 7 presents, respectively, the city-level distribution of vulnerability to flood risk for occupiers and owners for the 3000 French cities identified as exposed to flood risks. By applying our Digital Twin model to buildings and flood hazards, we find that 136,114 buildings are exposed to flood risk in our database. They are distributed among 109,282 owners NFCs and 101,184 occupiers NFC. Further details on exposure to different flood scenarios are provided in the Appendix, with the distribution of the number of establishments exposed to different flood scenarios in Figures 33 to 37.

For occupiers, the estimated economic impact of a centennial flood (medium return period scenario) approximately reaches almost 0.25 % of the French annual GDP (7 billion euros). This is primarily due to the concentration of large corporations in the area, which would be directly affected by flooding of the Seine. Île-de-France is also the region with the most potential damage in face of the most extreme scenario "Low return period floods" with damages amounting to almost 1 % of French annual GDP (see Figure 31 in the Appendix). In contrast, Figure 29 in the Appendix shows that Auvergne-Rhône-Alpes faces more damage from high-frequency floods than Île-de-France.

For property owners, the projected damages are significantly lower. Under a medium return period flood, losses are estimated at 0.005% of GDP, while the most extreme low return period scenario could result in damages of 0.02%, or approximately €500 million. In Europe, the flood risk stress tests have focused on the Netherlands, given its high exposure. For instance, in Caloia et al. (2023), the simulation of 35 flood scenarios leads to damages between 0.5bn and three bn euros for 3 million residential and 175,000 commercial properties.

The geographical distribution varies between owners and occupiers as damages vary between real estate and tangible assets, between sectors and with the number of establishments exposed. Among

Figure 7: Vulnerability to flood risk - Occupiers (left) vs Owners (right).



Note: This figure locates the establishment affected by at least one low return period flood. Colours show the distribution of the damage. Dark blue corresponds to damages close to the 10th decile, while light blue represents damages close to the first decile.

occupiers, Trade and Car repair firms are relatively more vulnerable (see Figure 8). This is due to the value of electrical and electronic equipment and vehicle inventories, and the fact that food stocks need additional treatment after a flood, but also because of the high number of establishments. Indeed, nearly half of food retail establishments are located in flood-prone areas Bremond et al. (2024). The Manufacturing sector is also highly exposed to medium return period floods because of expensive machines, as manufacturing is capital-intensive. However, the cost among owners of buildings is mostly supported by real estate firms. As this sector is highly leveraged and concentrated, this could still have consequences for the financial sector.[10]

[10]Nonetheless, a significant share of them could be Sociétés Civiles Immobilières (SCI), a common type of firm in France that is often used by non-real estate firms to manage their real estate assets. Since it is not possible to attribute these firms to their parent, we should underestimate the exposure of other sectors than real estate.

Figure 8: Potential damages for occupiers - Medium return period flood

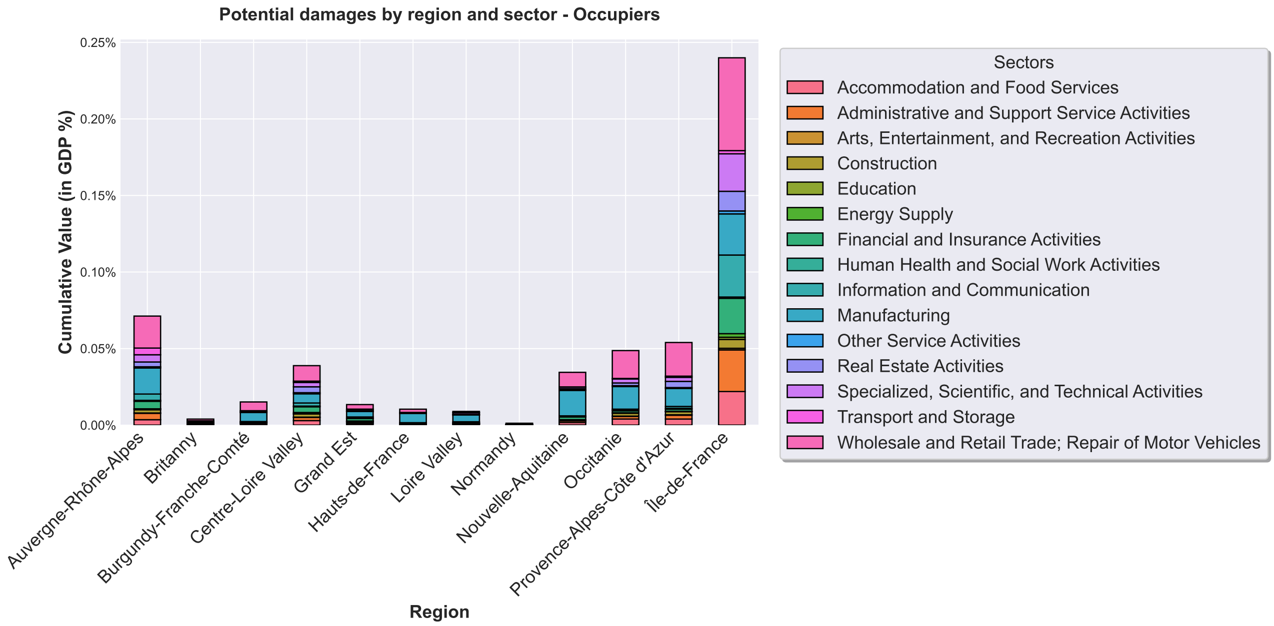
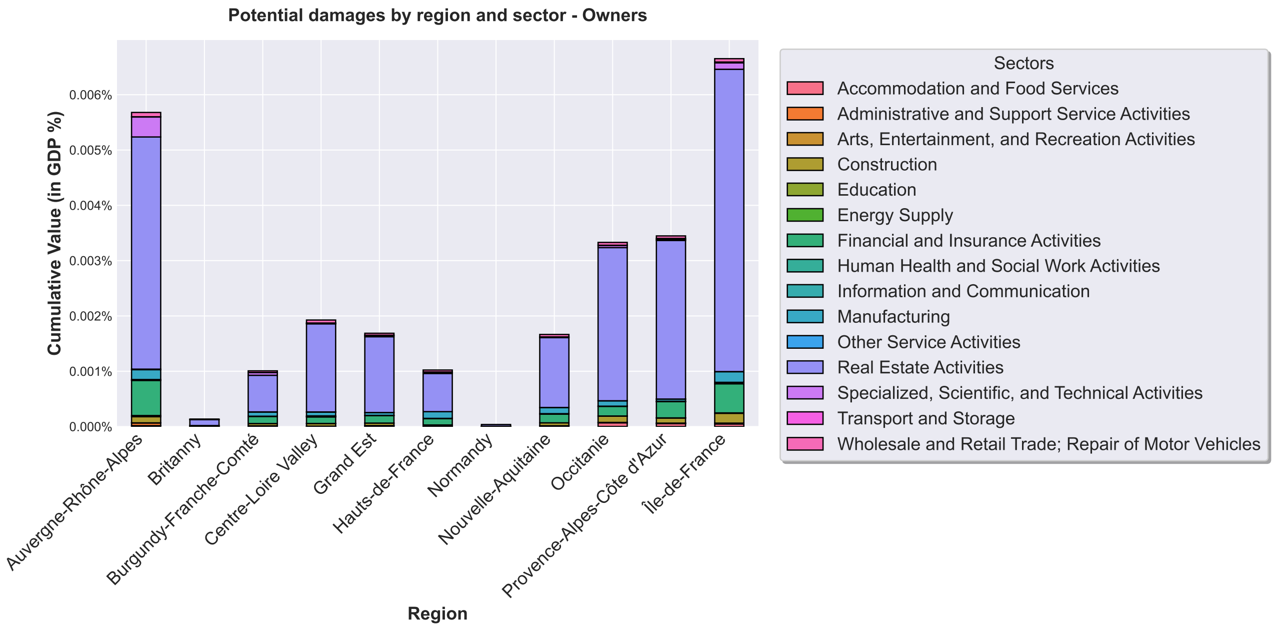
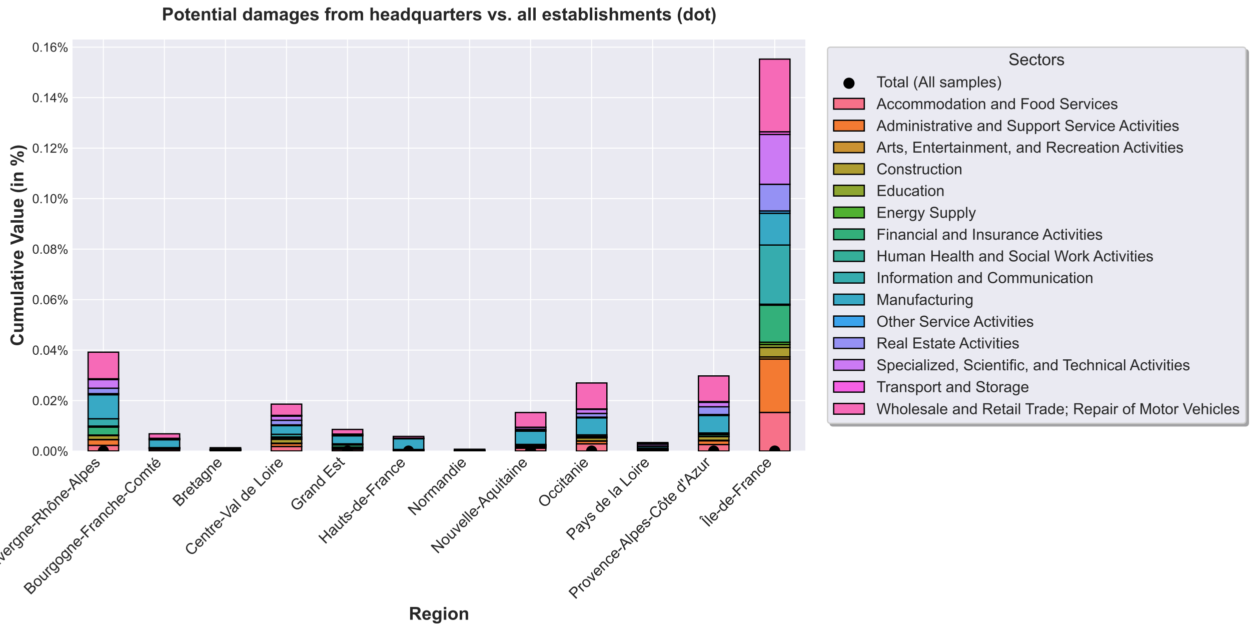


Figure 9: Potential damages for owners - Medium return period flood



Most of the analyses about firms' and the financial sector's exposure to flood hazards locate firms only at the headquarters level. However, we show in Figure 10 that limiting the data to only headquarters information would result in missing 1/3 of the potential damages from a medium return period flood. This highlights the relevance of our approach and the importance of going granular when assessing flood risks.

Figure 10: Potential damages - establishment vs headquarters (Occupiers)



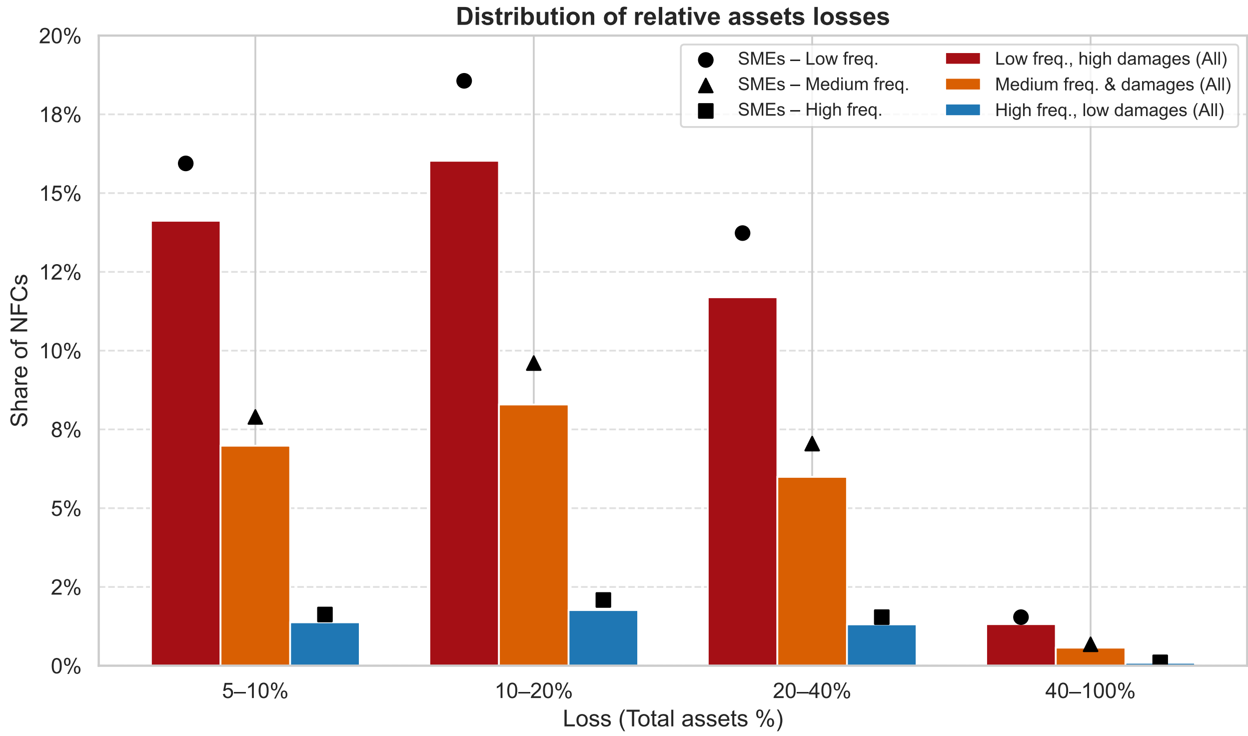
5.1.2 Potential damages distribution and leverage

As shown in the previous Section (see Figure 5), the average relative asset loss for owners is between 1 and 2 %. For users, it can reach between 8 and 13 % depending on the flood scenario before insurance compensation. Taking into account insurance compensation, the losses would be less than 1 % for owners and between 1 and 2 % for occupiers, which is in line with Fatica et al. (2022).

However, some firms may be more vulnerable to important floods. We define vulnerable firms as those for which the losses would represent 10% of their total assets. While only 3 % of NFCs would be in this category after a high frequency flood, this figure would reach 28 % with a low frequency flood. SMEs are more exposed, as 33% of them are vulnerable to a low frequency scenario (return period > 1000 years), as shown in figure 11. To contextualise this result, Keiller and Van Reenen (2024) find that natural disasters reduce capital by 12 p.p. and increase firm exit by 2 percentage points using the international EM-DAT database.

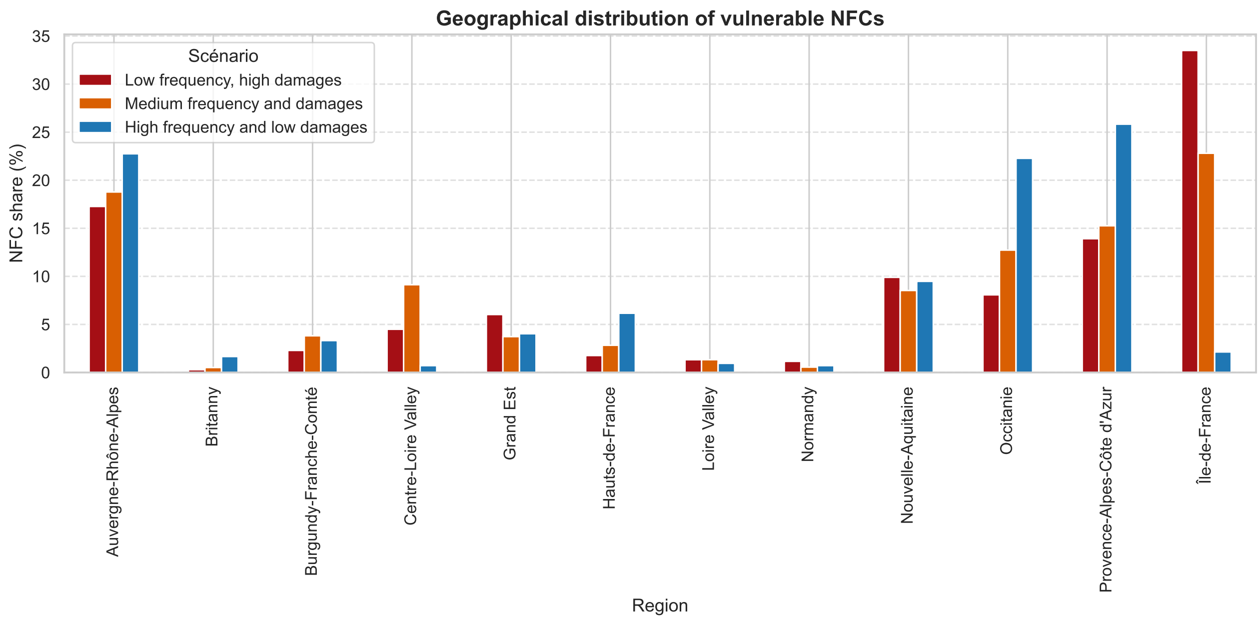
The distribution of vulnerable firms varies widely across regions and sectors. Regional vulnerability of these firms at risk depends on the frequency of floods. Vulnerable firms to high-frequency floods are more numerous in Auvergne-Rhône-Alpes. However, the share of vulnerable firms to medium and low frequency floods is the highest in Île-de-France (Figure 12). The vulnerability also highly depends on the sector, as shown in Figure 13. Vulnerable NFCs are mostly in the Accommodation & Food, Construction, Manufacturing, Trade and Car repair sectors.

Figure 11: Relative losses for NFC



Note: This figure plots the distribution of damages as a % of total assets (real estate and equipment) for firms affected by at least floods of low period of return.

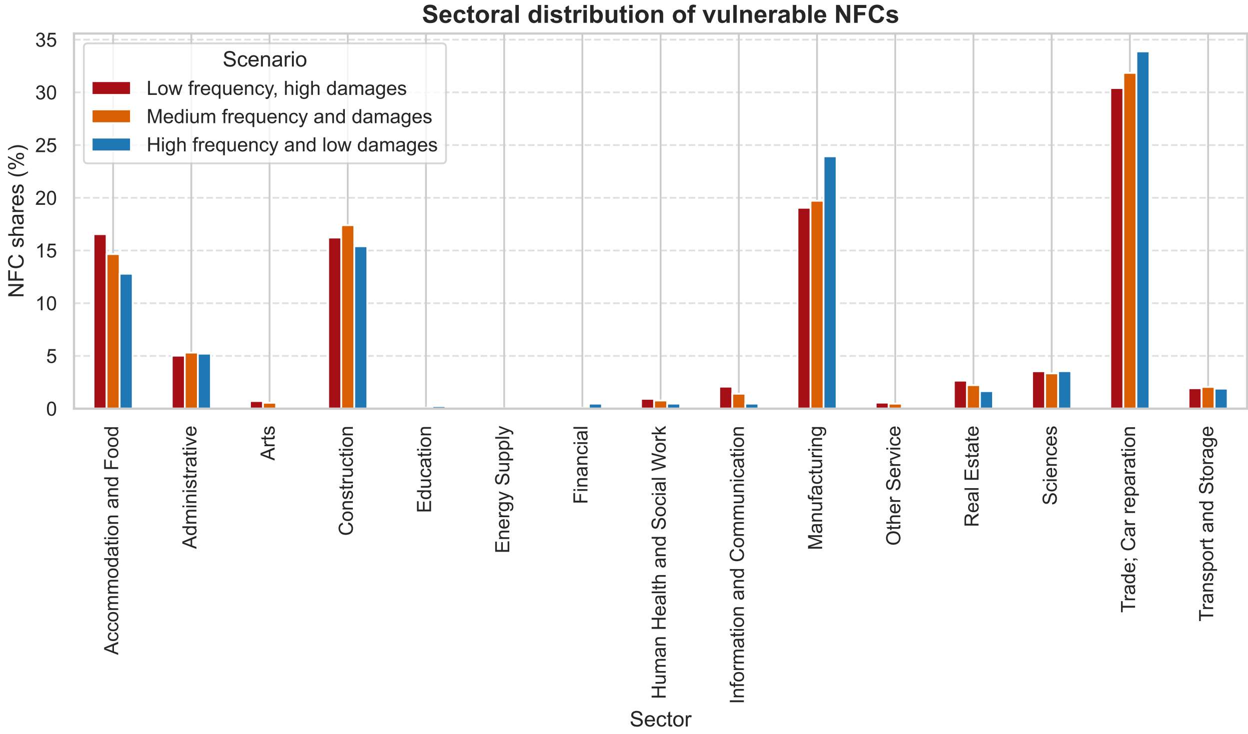
Figure 12: Relative losses for NFC - region



Note: This figure plots the share of vulnerable NFCs in each sector, defined as firms with potential losses representing more than 10 % of total assets (real estate and equipment).

Extreme flood events can substantially affect the leverage distribution and thus the credit risks for the banking system. Figure 14 shows how the leverage distribution, defined as the distribution of total

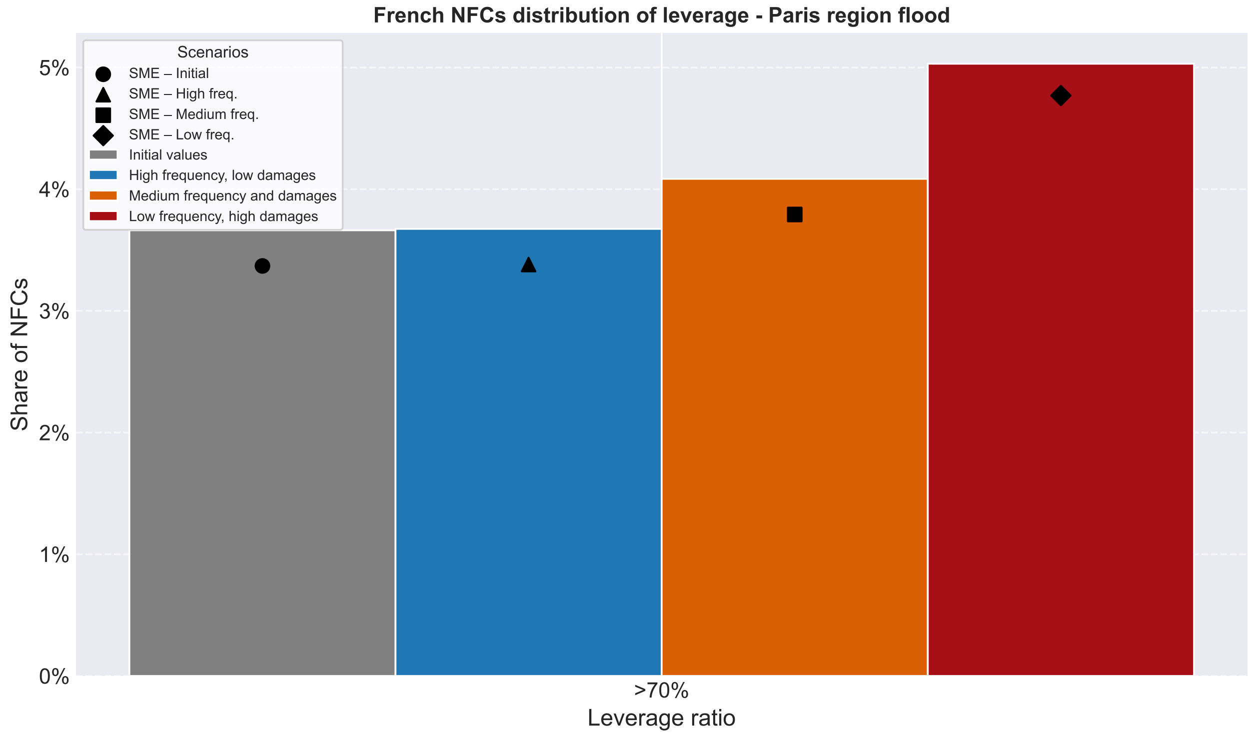
Figure 13: Relative losses for NFC - section



Note: This figure plots the share of vulnerable NFCs in each sector, defined as firms with potential losses representing more than 10 % of total assets (real estate and equipment).

financial debt on total assets, moves when a regional flood event materialises. While the distribution is only slightly affected by a high-frequency flood, a medium-frequency flood, which corresponds to a centennial flood of the Seine, has a significant impact. The share of NFCS with leverage higher than 70% moves from 3.5 to 4% for a centennial scenario and to 5% for a more extreme scenario, which remains moderate for the NFCS sector but is important at the individual level as only 7% of our sample are exposed to floods.

Figure 14: Relative losses for NFC - section



Note: This figure plots the leverage distribution, defined as the distribution of total financial debt on total assets under different scenarios. Around 350,000 firms have balance sheets available in our database. Among them, 7% are exposed to flood risk.

5.2 Credit risk

In this section, we assess the resilience of the banking sector to the materialisation of medium return period floods by region. As Caloia et al. (2023) and Lepore and Fernando (2023), we assess the impact on banks' real estate exposures through the impact on the value of the collateral, but we complement their approach by analysing the impact through occupiers' credit risk. We show that, even if occupiers need to be insured against flood risk, while it is not the case for owners, as the damages for occupiers are much greater than for users, the transmission to the banking system is not negligible.

Table 4 in the Appendix shows descriptive statistics for the loans data from AnaCredit. Exposures to owner firms exposed to floods and to occupiers exposed to floods represent, respectively, €92 billion (among a total exposure of €917 billion). We also show the share of mono establishments in this credit register database by type of NFCs.

5.2.1 From potential losses to the rise of probability of default

Table 2 shows the results of the model described by (4) with alternative specifications to explain the probability of default, the value of which is between 0 and 1. Model 1 is the standard model as in Lee (2024) or Emambakhsh et al. (2023). Firms with higher leverage, measured as total debt/total assets, have a significantly higher probability of default. When controlling for macroeconomic environment with time fixed effects in model 3, we observe that an increase in cash ratio significantly lowers the probability of default and that profit is also negatively correlated with the probability of default. The relationship signs are in line with economic theory and previous analysis (Emambakhsh et al. (2023), Lee (2024)). They are robust when we replace the time fixed effects with sector*time fixed effects in Model 4.

Table 2: Credit risk pricing models

	Model 1	Model 2	Model 3	Model 4
Leverage	0.15***	0.15***	0.13***	0.12***
	(0.02)	(0.02)	(0.01)	(0.01)
Profit	−0.03	−0.02*	−0.01	−0.01
	(0.01)	(0.01)	(0.02)	(0.01)
Cash ratio		−0.04	−0.04**	−0.03**
		(0.03)	(0.01)	(0.01)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects			Yes	
Sector Time Fixed Effects				Yes
Num. obs.	1256661	1256661	1256661	1256661
Num. NFC	352817	352817	352817	352817
R^2	0.67	0.67	0.68	0.69

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors are clustered at the year-department level

5.2.2 Expected losses for owners

We evaluate expected losses from a medium and low frequency flood at the regional level by simulating damages on the collateral for NFCs having establishments in the affected region. Bank loans to owners exposed to flood risk represent a significant share of credit: €91 billion or 10% of total credit amount. However, we identify that the banking sector's expected losses are contained (Figure 15) for several reasons. First, our damage functions give more weight to building structures than to technical equipment. Second, the probability of default of owners is initially low, and the median increase due to flood damage is also small, in line with Caloia et al. (2023) and Lepore and Fernando (2023). Figure 16 shows that the median increase is lower than 1 basis point, and for the third quartile, around 1 basis point. Third, the Loss Given Default is also initially low because owners' loans in our sample are collateralised by high numbers and value of protection. We plot the LGD changes distribution for LGD affected by the flood (Figure 16) as percentage points. In the total sample of owners, only 14% of loans have a positive LGD. This share increases to 17% of loans if we simulate a flood shock to exposed owners. For these reasons, losses would only amount to up to 6 or 4 million euros, respectively, for a low return flood in Île-de-France or Auvergne-Rhône-Alpes (around 0.02 basis points of total banking system risk-weighted assets).

Figure 15: Loss from owners

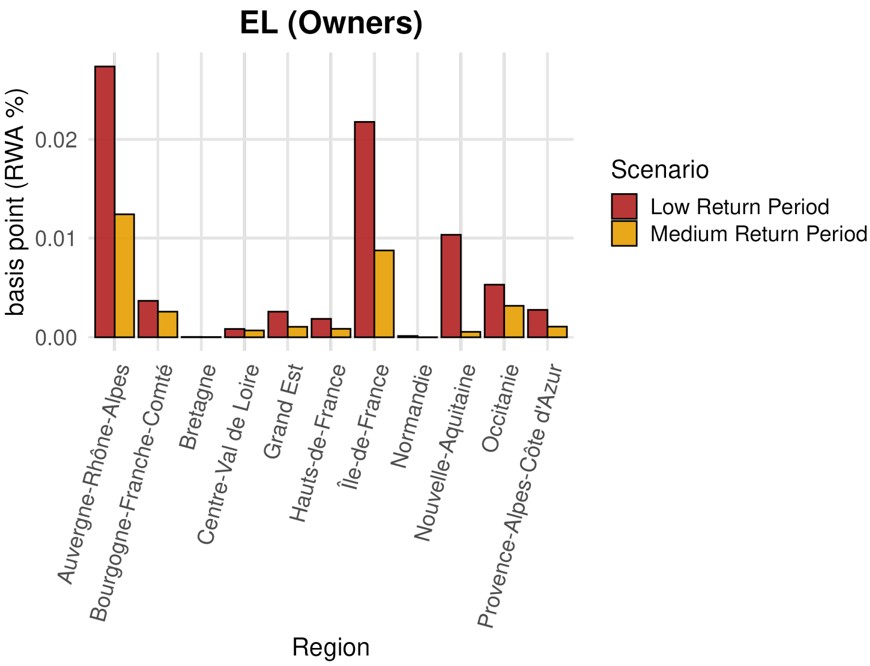
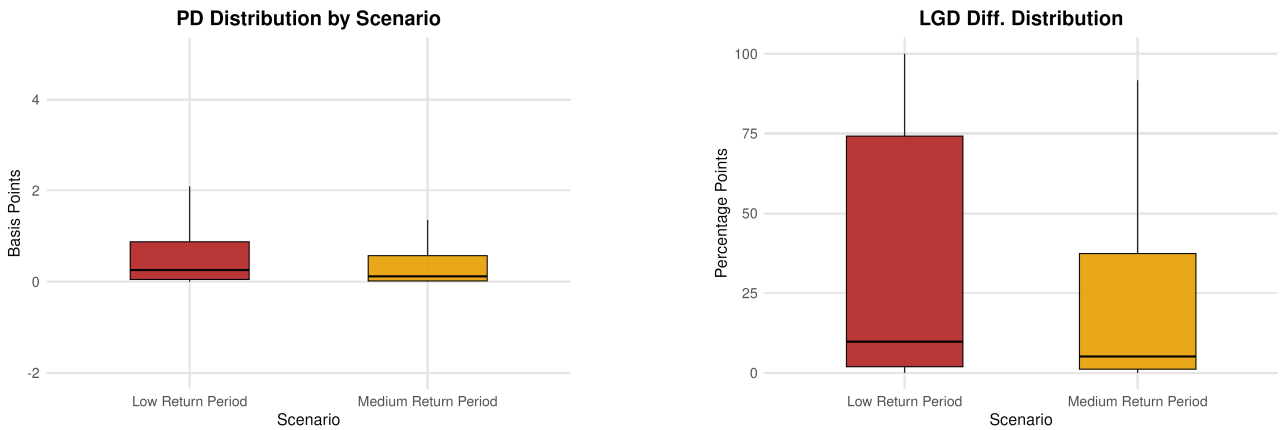


Figure 16: PD and LGD Distribution - Owners



5.2.3 Expected losses for occupiers

In this section, we evaluate the banking sector's expected losses along two hypotheses: 1) a baseline scenario: no profit loss, 2) profit loss: where EBIT is reduced by 10 % before insurance compensation[11]. With both hypotheses, we simulate a shock to the leverage from the flood, as from our regression on historical floods, physical assets are more significantly affected than cash (see 4). We find that bank expected losses from occupiers are higher (Figure 18) than through mortgages from owners before taking into account the insurance system for several reasons. First, the damages per firm are higher when the firm is using the real estate asset than when it is only owning it, as the damage cost on real estate is, on average, lower than on the technical equipment. Second, the probability of default is

[11] In our analysis about past data, we find that the profit loss is around 1 % but within the year of balance sheet the firm can receive the insurance compensation

more affected for occupiers, also because the damages weigh more on their debt. Insurance protects NFCs and the banking sector from flood risk, but with the actual insurance level,[12] there could still be some loss in the banking sector.

Figure 17: PD distribution - Occupiers

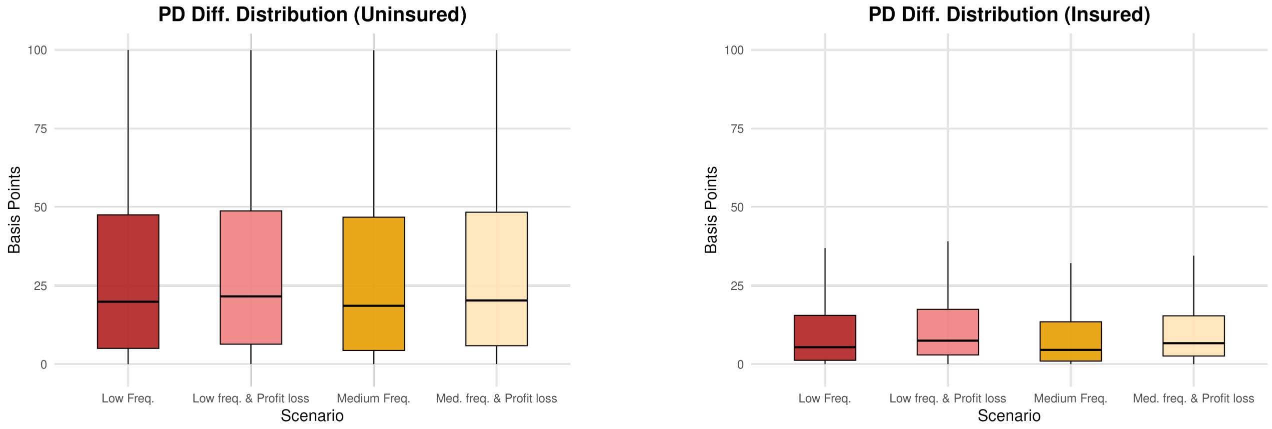
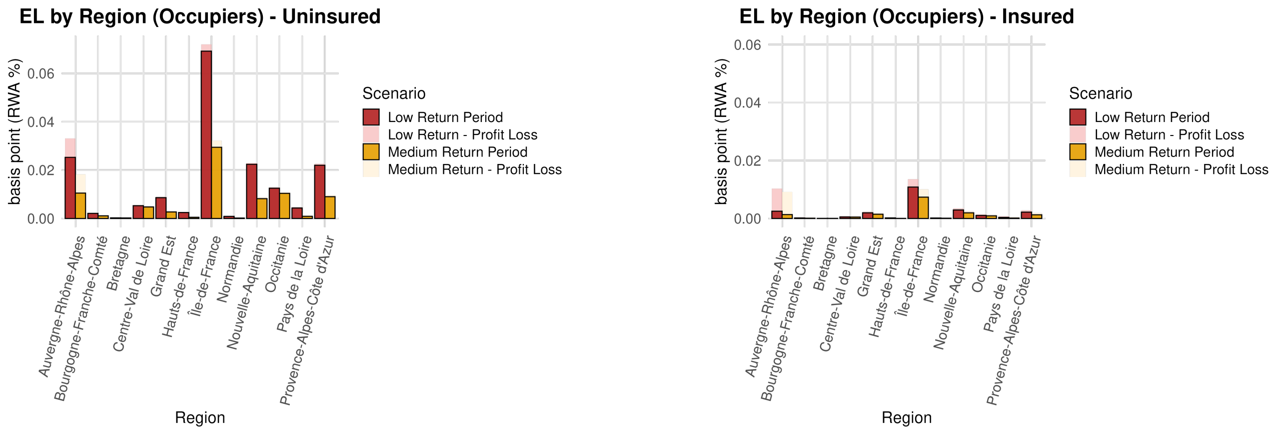


Figure 18: Losses Occupiers

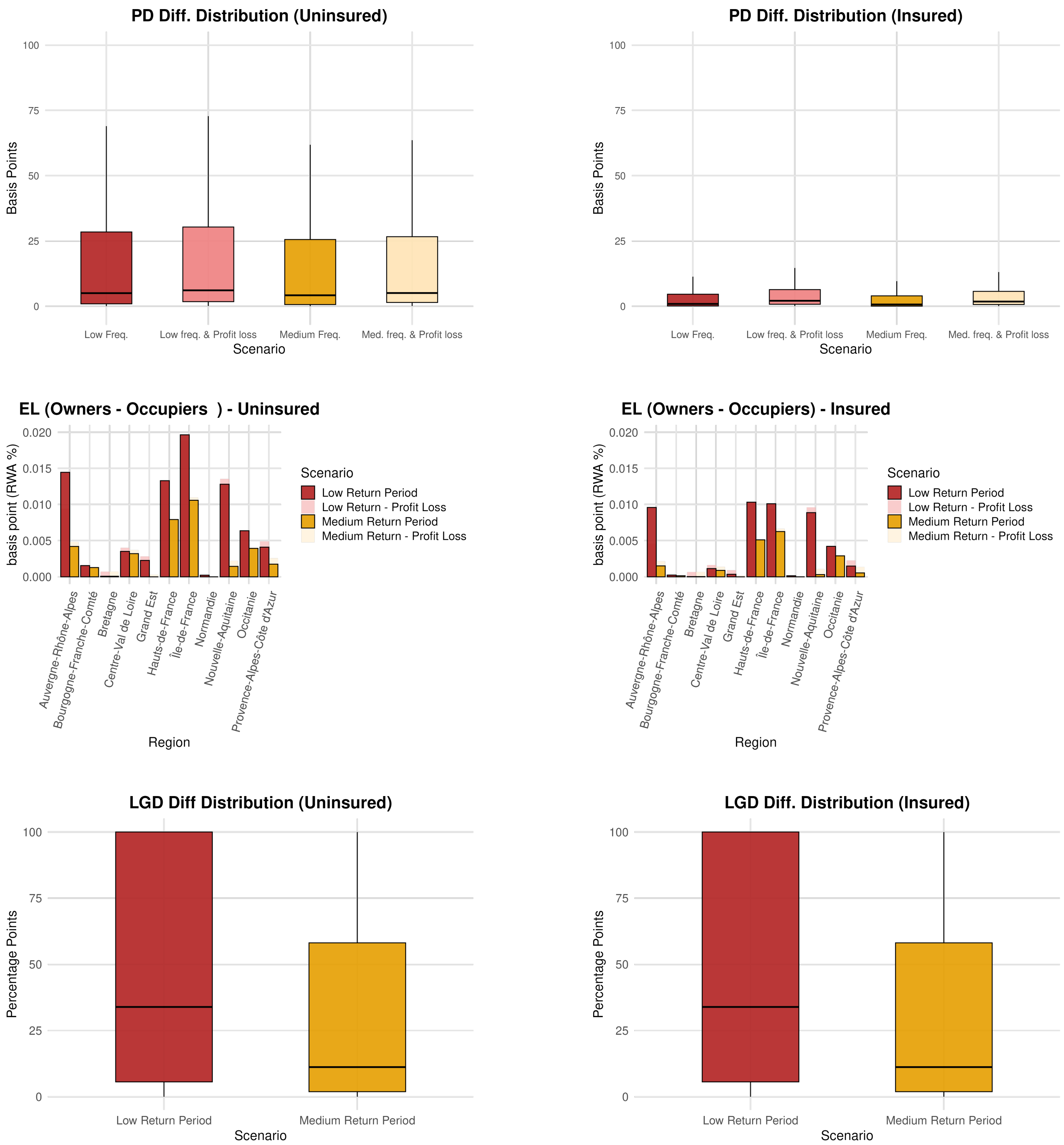


5.2.4 Expected losses for owners-occupiers

We also compute the expected loss from owners-occupiers, as vulnerabilities can amplify the impact on their credit risk. Indeed, they are both affected through their LGD and PD. However, when we aggregate the potential loss from their loans at the banking system level, it remains contained.

[12]We consider that NFCs only pay 10 % of the cost, as it is in the current insurance contracts.

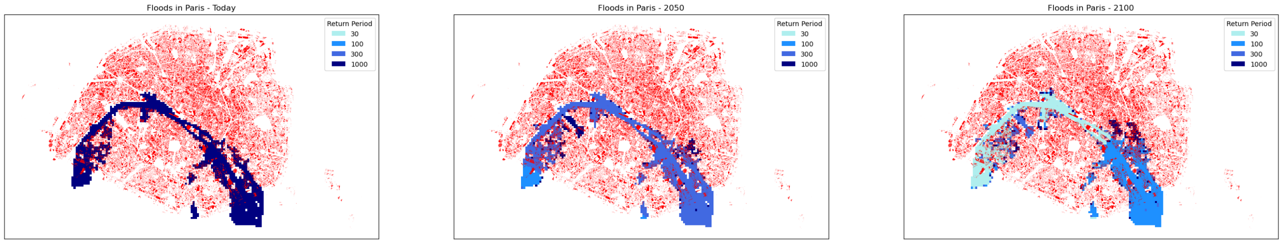
Figure 21: Owners - occupiers



5.2.5 Climate-related capital buffers

As suggested by Bartsch, Busies, Emambakhsh, Grill, Simoens, Spaggiari, and Tamburrini (Bartsch et al.), projected losses unanticipated by the actual estimation of PDs and LGDs by banks can then be used to determine a bank climate SyRB, also expressed as a percentage of RWA. Since, according to EU law, the SyRB has to be set in steps of 0.50 percentage points (cf. Article 133(9) CRD), the current estimation is too low to lead to the implementation of a buffer. However, as explained in the next Section, climate change increases flood occurrence and could lead to an accumulation of damages, amplifying firms' financial vulnerability against which banks will have to build resilience.

Figure 22: Flood hazards in Paris



(a) Today (b) 2050 (c) 2100

Note: Different shades of blue indicate increasing probability of occurrence (the lighter the more frequent with 30-year return period, the darker zone corresponds to a 1000-year return period.

6 Climate change, insurance coverage and projection data

The potential losses highlighted above are computed using flood scenarios based on past data related to past climate conditions. Nonetheless, climate change increases precipitation and, thus, flood occurrence. To take these evolutions into account, we plug projection data on flood hazards into our model. This enables us to compute potential future damages depending on emissions pathways. To understand how much of these damages will be borne by firms (and potentially cascading to bank losses), we make assumptions on the evolution of the insurance coverage, i.e. the share of damages that are borne by insurance.

6.1 Climate change and projection data

We start by computing damage forecasts by changing the hazard dataset: instead of current hazards, we input projection maps provided by Delft University (Paprotny and Morales Nápoles, 2016). The RAIN Pan-European gridded data sets provide probabilities of occurrence for river floods under both present and future climate conditions across Europe. Under different climate scenarios, the maps cover three distinct periods: 1971–2000 (representing the historical baseline), 2021–2050 (mid-century projections), and 2071–2100 (end-of-century projections). We focus on the worst-case scenario, i.e. RCP 8.5, a high-emissions climate change pathway that projects global warming of about 4.3C by 2100.[13] The projections of flood hazards in Paris (using RCP 8.5) at different periods are mapped in figure 22). Different shades of blue indicate an increasing probability of occurrence (the lighter, the more frequent).

The most striking aspect of these projections is not the expansion of the "very severe" zone (represented by dark blue areas in the historical flood map, indicating a 1 in 1000 annual chance of occurrence) but rather the dramatic increase in the frequency with which these zones will be affected. By 2050, most of this zone will have a 1/300 chance of being flooded, and by 2100, it will be 1 in 30. Regarding the impact of climate change on floods in Paris, it seems to be more their frequency rather than their geographical extent that will significantly grow.

In terms of the distribution of damages, this change can be conceptualised not so much as an upward shift of the curve (more damages when very rare events strike) but rather as a rightward shift (more frequent, very destructive events). Consequently, focusing solely on the increase in the right tail

[13]These maps do not take into account the potential aggravation of land take and soil artificialisation, which would lead to their impermeabilisation and therefore to the worsening of floods.

of the distribution captures only a tiny part of the overall change. This is why our analysis considers not just maximum damages but average damages $\hat{D}$, calculated as follows:

$$\hat{D}_t = \sum_i P_i * D_{i,t} \tag{11}$$

Where P_i is the annual probability of occurrence (low, medium, or high) and D_i, t are the associated damages for period t.

$$\hat{D}_t = P_{low} * D_{low,t} + P_{medium} * D_{medium,t} + P_{high} * D_{high,t} \tag{12}$$

To obtain these D_i, t, we run our Digital Twin model exactly the same way to compute damages for each time horizon. By doing so, we modify the hazards but make the assumption that exposures will not move, i.e. that firms will not spatially relocate. While this assumption might appear very strong, the upcoming context of land scarcity in which NFCs are expected to operate under increasing land restrictions de L'Estoile and Salin (2024) might affect their ability to move. One interesting result is that, under the current climate, damages with the Delft data are lower than with the Géorisques data. The latter has a better spatial resolution than the one from the RAIN project; this is another argument for more granularity.

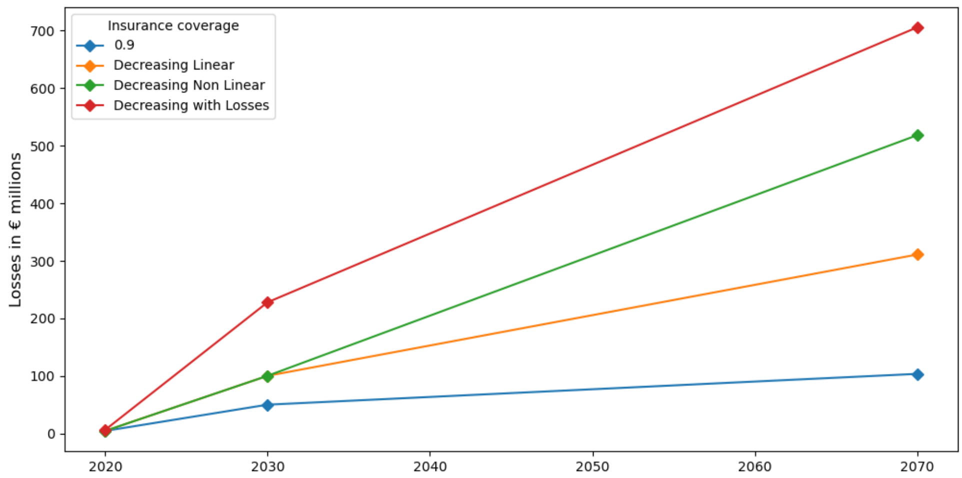
6.2 Simulation of the aggregate insurance coverage

We then insert our calculated $\hat{D}_t$, as explained in section 3.3, into the $C_t^f = \hat{D}_t * (1 - \alpha_t)$ equation. It is, however, challenging to match our data with granular data on insurance coverage, especially regarding the future evolution of insurance gaps. Thus, we derive scenarios regarding both the level and the dynamics of α_t. The simpler case would be a time-unvarying α, which can be based on EIOPA's data (0.9). More realistic cases could imply an increasing α_t, being linear ($\alpha_t = \alpha_0 - \beta * t$) or non linear ($\alpha_t = \alpha_0 - \beta * t$š) . The last scenario proposed here (but there could be many others) is an α_t whose increase is proportional to the losses ($\alpha_t = f(D_t) = \alpha_0 * exp(\beta * D_t)$). This would mean that the growth of losses leads insurance companies to increase their premia or to withdraw from the market.

Figure 23) displays the different C_t^f evolutions deriving from these calibrations.

This analysis enables us to take into account the role of insurance in mitigating the losses that firms face, but also to simulate different scenarios regarding the level and the evolution of insurance coverage gaps. It could be complexified by introducing heterogeneous NFCs with vulnerable firms for which the α_t is larger or/and increases more over time. The analysis could also be used to derive the differentiated transmission of firms' losses to credit risk metrics according to the insurance coverage pathways.

Figure 23: Average Annual Losses for Firms Over Time in Paris - User firms



Lecture note: At each time period t, average damages are computed by multiplying the severity of floods with their probability of occurrence. These average damages are then multiplied by α_t, a coefficient of insurance coverage. Several scenarios regarding the evolution of α_t are tested.

7 Conclusion

This paper simulates flood-related damages on firms' physical assets and their propagation to the financial system. It relies on a newly developed Digital Twin tool that shares three main innovations: integrating very granular datasets, distinguishing property and transferable assets, and identifying clear transmission mechanisms of climate hazards to banks *via* firms. By locating the flood at the establishment level, we find that buildings and firms (owners and occupiers) are exposed to significant flood damage. These could turn into significant losses for firms, which may seriously impair firms' assets, especially for those that are highly indebted.

Our findings show that losses associated with transferable assets are much greater than those affecting properties. In that sense, the *contents* matter more than *containers*. However, the risks associated with a decrease in the value of impacted collateral are not neglectable. It is important to bear in mind that most of the hazard data we use for the moment reflects flood probabilities of occurrence based on past data. Continuing the incorporation of projection data would certainly worsen the picture. This work thus opens the floodgates to numerous subsequent analyses. Investigating the role of insurance and its sustainability pathways seems to be a promising waterway, although it would require more detailed data.

The newly developed Digital Twin also provides a ready-made infrastructure for designing climate-adjusted stress test scenarios at a granular level, enabling supervisors to identify vulnerable portfolios. Thus, our work contributes both to the micro and macroprudential literature. Our tool can be used by microprudential authorities to monitor climate risk at the individual level, but also to calibrate macroprudential tools. Indeed, the increase in flood frequency could lead to systemic risk amplification through the leverage ratio of NFCs. Thus, we have explained that, even if we do not assess the need for a systemic risk buffer as the expected losses remain contained in our analysis, our framework could be used to calibrate such a tool.

Our methodology also provides a fully-fledged, adaptable tool for assessing climate physical risk outside the financial realm. For instance, it has been used by the United Nations Office for Disaster Risk Reduction (UNDRR) in their 2025 Global Assessment Report to assess the potential flood-related losses of the tourist and cultural sectors in Paris (for Disaster Risk Reduction, 2025). Finally, by simulating future floods under climate change, the model quantifies the costs of inaction — "no transition" and "no adaptation" — that could be compared to the costs of investing now in transition and resilience. These comparisons thus give policymakers a concrete cost–benefit analysis, with a fine identification of winners and losers at the sector/firm level.

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A Damages from past floods

A.1 Descriptive statistics

To estimate the impact of exposure to past floods on real estate and equipment, we restrict our sample to single establishment firms, accounting for around 80 % of firms in Fiben. Focusing on single establishment firms allows us to analyse granularly the impact at the establishment level. We will also analyse the effect on multi-establishments in robustness' graphs. We keep firms that declare data over at least three consecutive years. The gross value of assets corresponds to their historical value adjusted by accounting reevaluations.

Table 3: Descriptive Statistics - Fiben

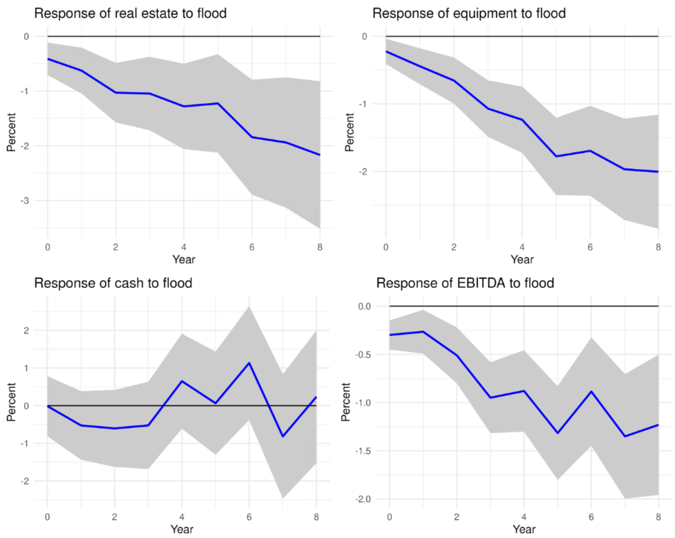
Variable	Mean	SD	P10	P25	P50	P75	P90
Construction Share (%)	12	19	0	0	4	15	35
Equipment Share (%)	21	18	1	6	19	32	48
Total Asset (Thousands euros)	20544	566333	600	1001	2031	5237	15481
Employment	33	777	2	6	12	27	53
Cash Ratio (%)	10	10	0	2	6	14	25
ROA (%)	9	3	0	4	8	14	21
Leverage (%)	20	2	0	4	13	27	48

B Loans with physical collateral (AnaCredit - 2023)

Table 4: Descriptive Statistics Comparing All, owners and occupiers

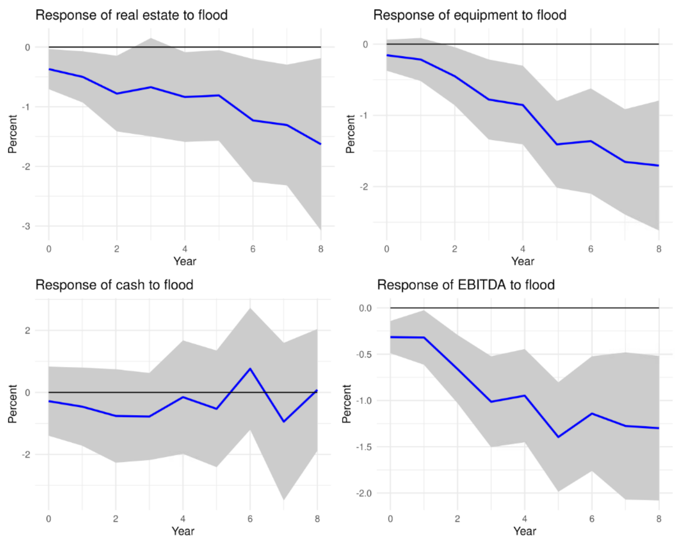
Statistic	All	Owners	Occupiers
Average probability of default	0.046	0.015	0.041
Average LGD	0.107	0.103	0.181
Total outstanding (Million euros)	919991	90829	74462
Average outstanding (euros)	198809	794146	518577
Average protection (euros)	843670	4014009	1592977
Average real estate protection (euros)	365884	2147183	596648
NFCs (N)	1718613	42495	35963
Instruments (N)	4627521	114373	143589
Mono-establishment share	85 %	83 %	72 %

Figure 24: Effect on real estate and transferable assets - Main - Conley



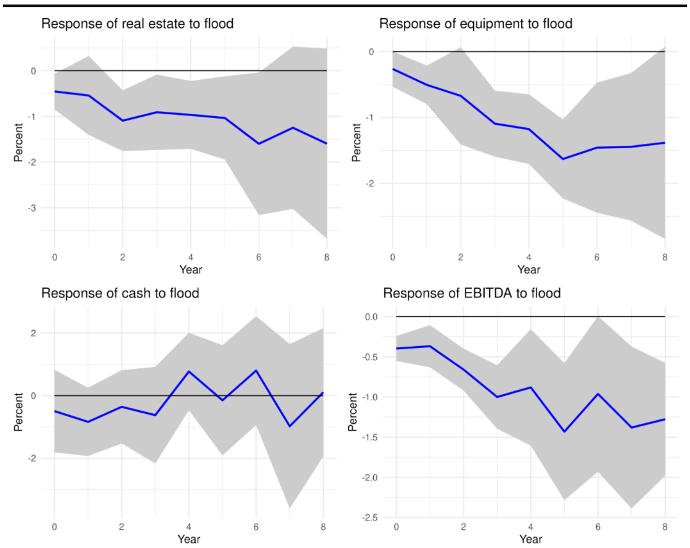
Note: impulse response to a flood shock. The sample is 1992 - 2023. 90 % significance bands displayed. Mono-establishment only.

Figure 25: Effect on real estate and transferable assets - Sector by time fixed effects



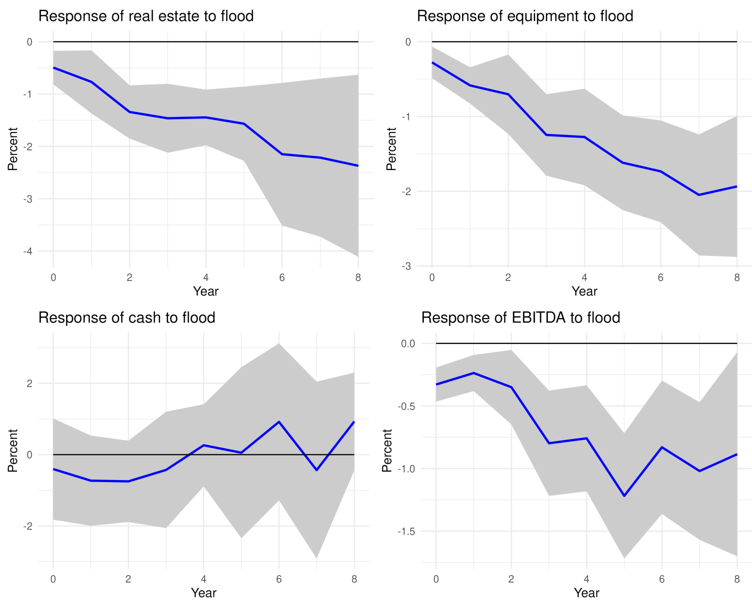
Note: impulse response to a flood shock. The sample is 1992 - 2023. 90 % significance bands displayed. Mono-establishment only

Figure 26: Effect on real estate and transferable assets - Single flood only



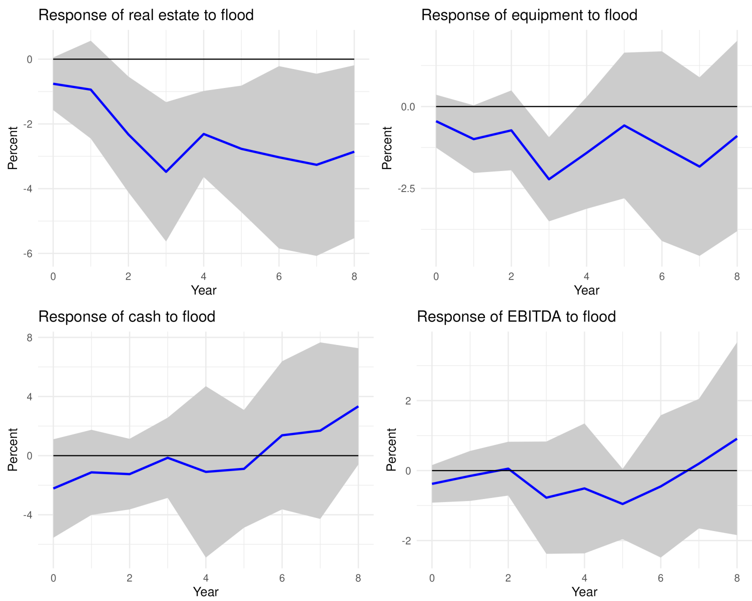
Note: impulse response to a flood shock. The sample is 1992 - 2023. 90 % significance bands displayed. Mono-establishment only.

Figure 27: Effect on real estate and transferable assets - All firms



Note: impulse response to a flood shock. The sample is 1992 - 2023. 90 % significance bands displayed. Multi-establishment firms.

Figure 28: Effect on real estate and transferable assets - All firms



Note: impulse response to a flood shock. The sample is 1992 - 2023. 90 % significance bands displayed. Multi-establishment firms .

C Potential damages by section and region - High return period floods

Figure 29: Potential damages for occupiers- High return period floods

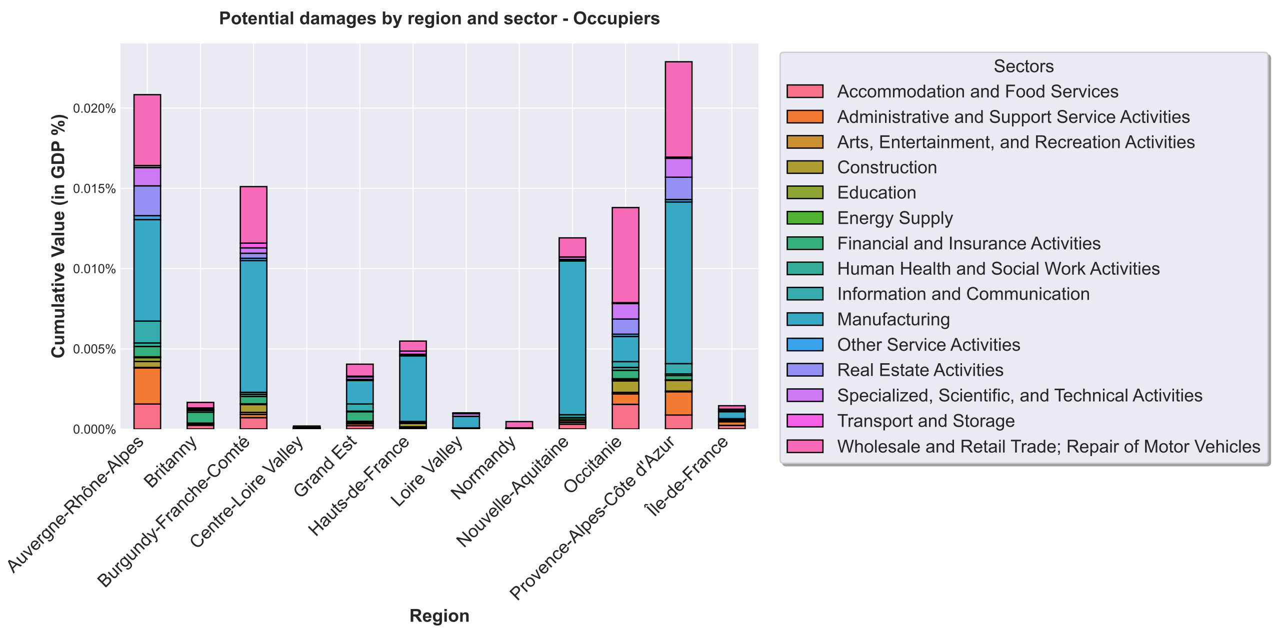
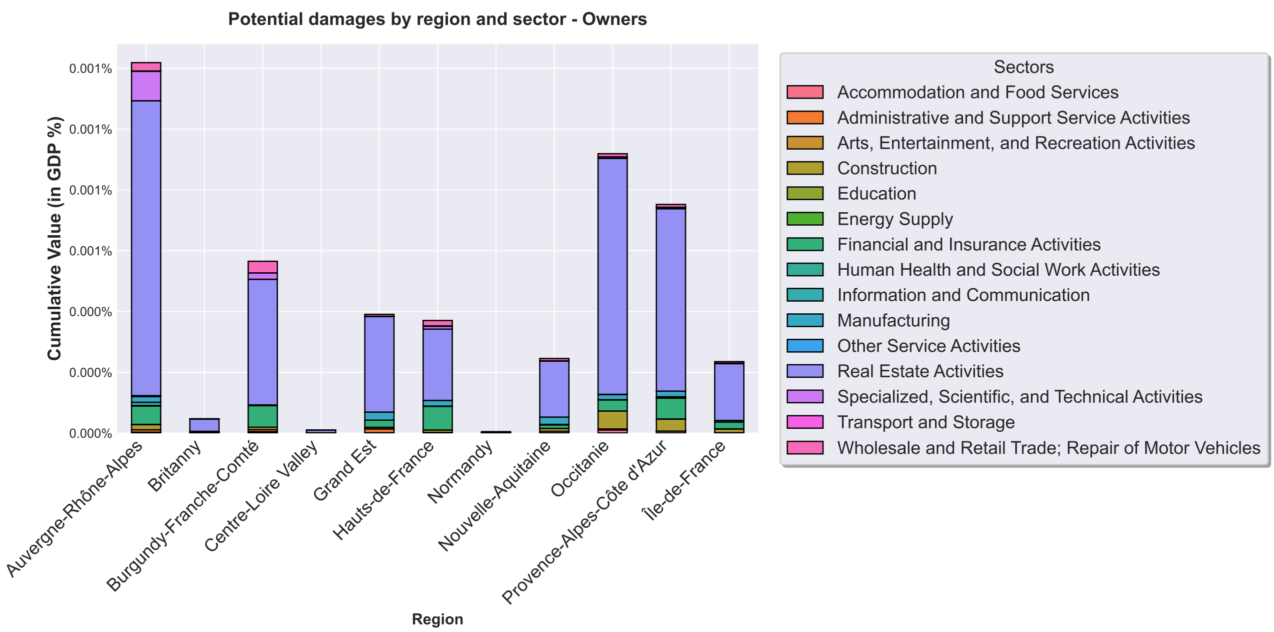


Figure 30: Potential damages for owners - High return period floods



D Potential damages by section and region - Low return period floods

Figure 31: Potential damages for occupiers- Low return period floods

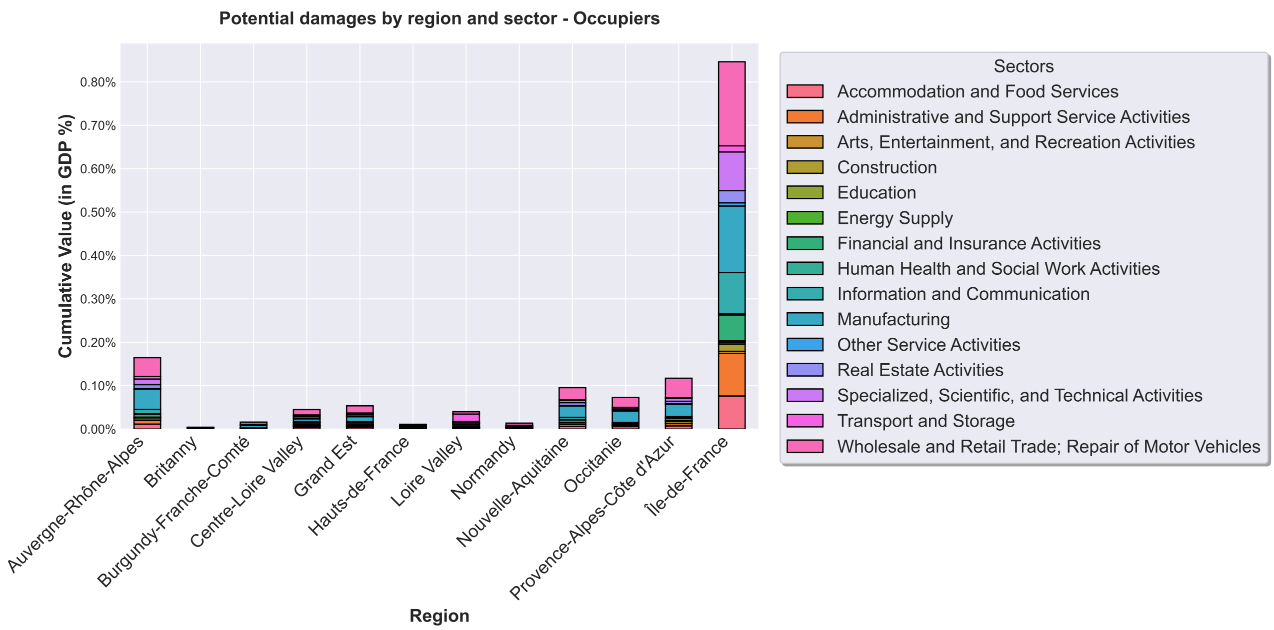
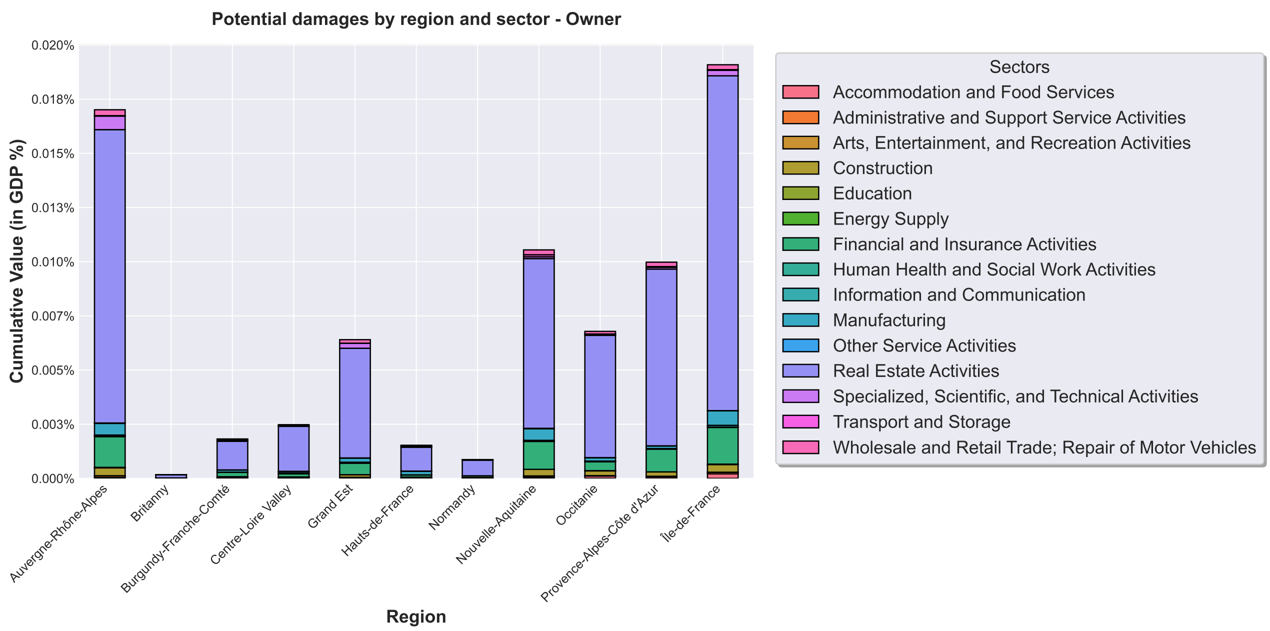


Figure 32: Potential damages for owners - Low return period floods



E Establishment affected by section and region - High return period floods

Figure 33: Potential damages for occupiers- High return period floods

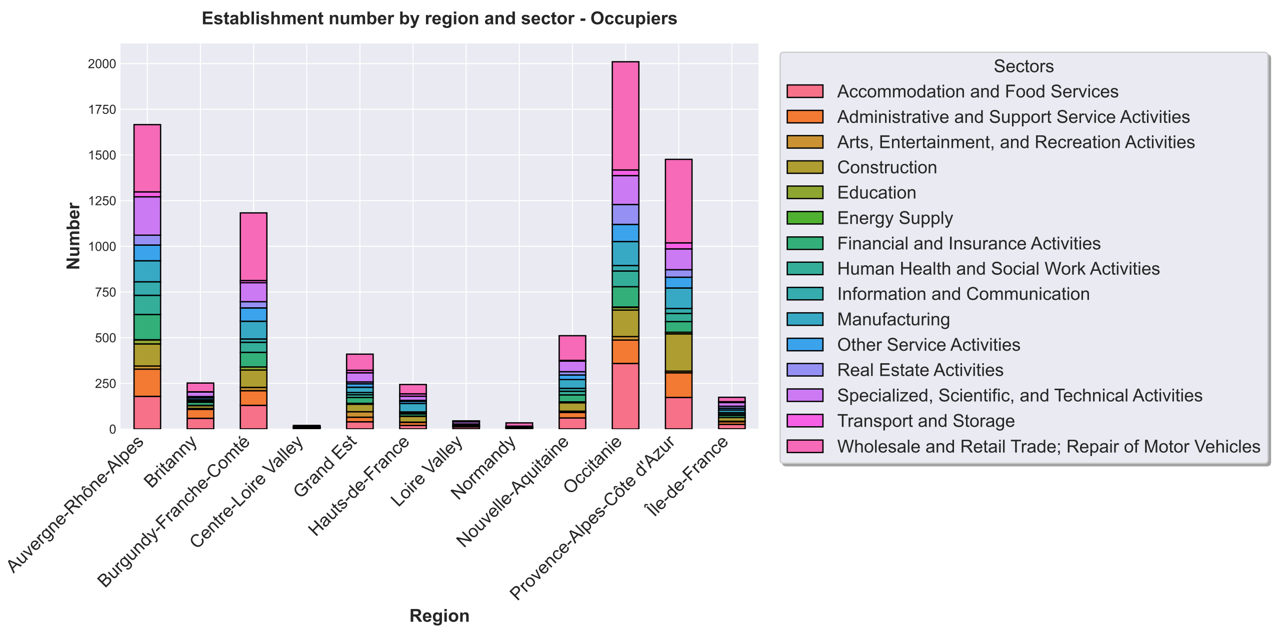
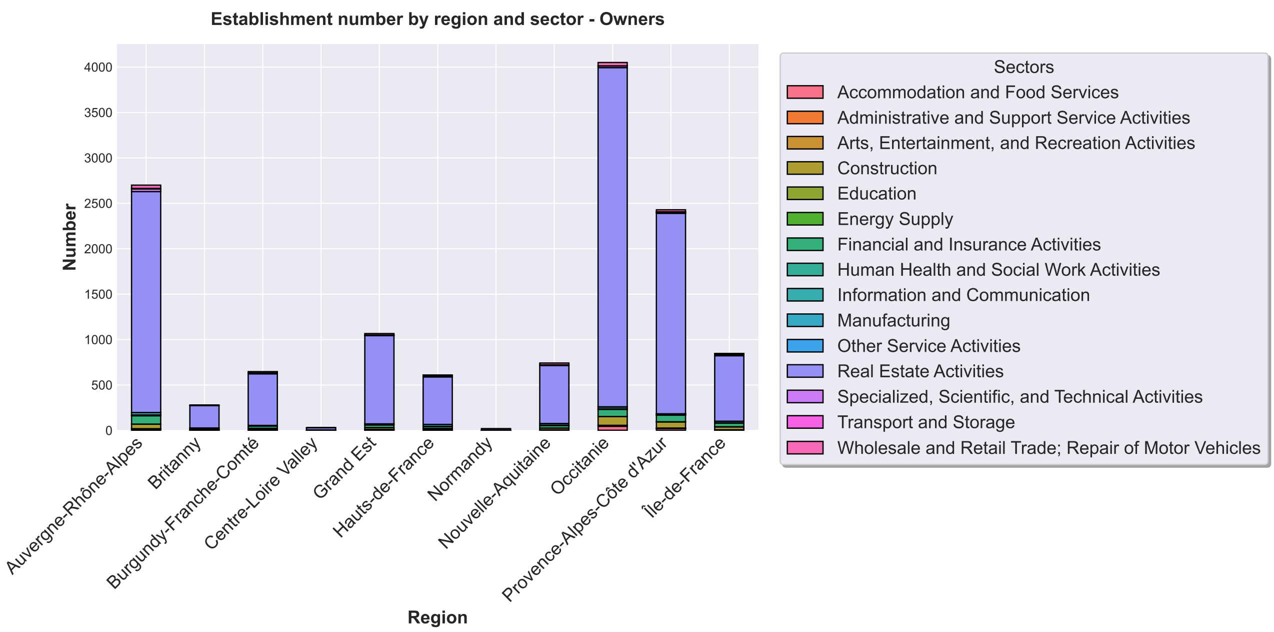


Figure 34: Potential damages for owners - High return period floods



F Establishment affected by section and region - Medium return period floods

Figure 35: Potential damages for occupiers- Medium return period floods

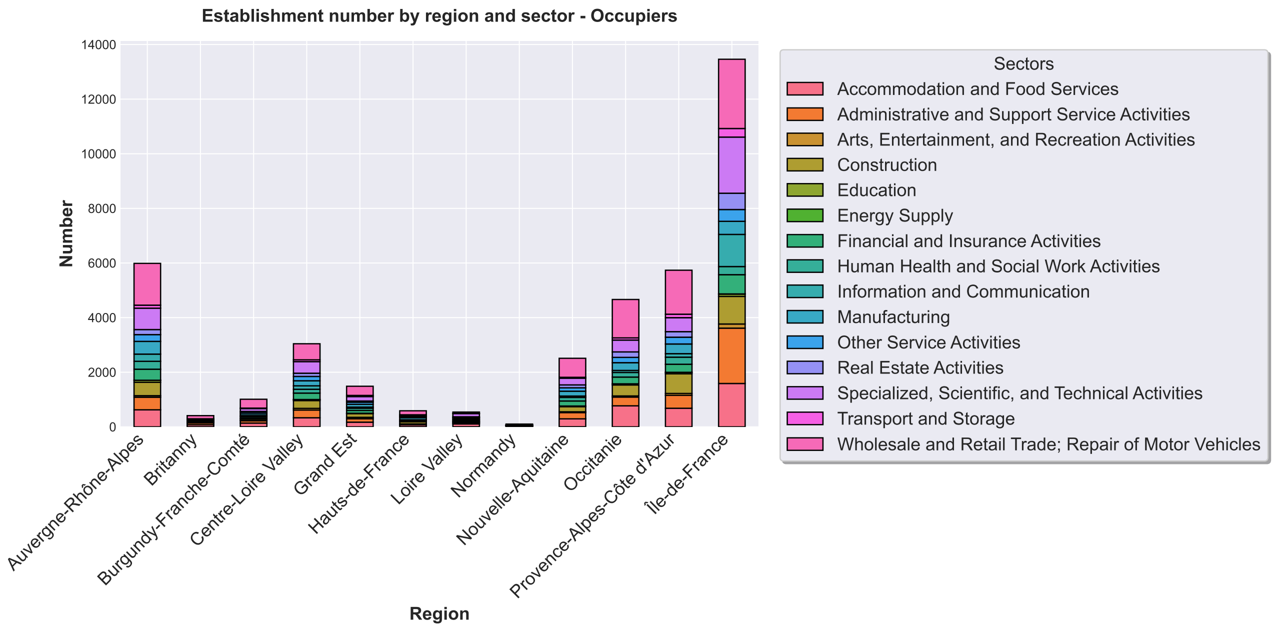
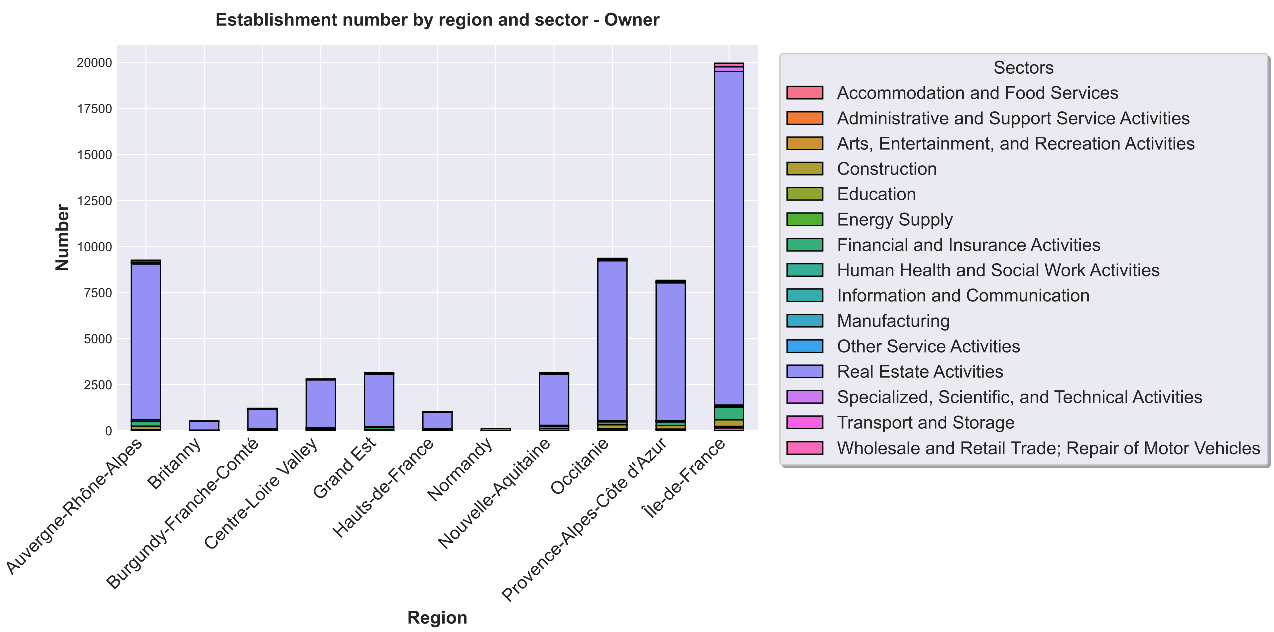


Figure 36: Potential damages for owners - Medium return period floods



G Establishment affected by section and region - Low return period floods

Figure 37: Potential damages for occupiers- Low return period floods

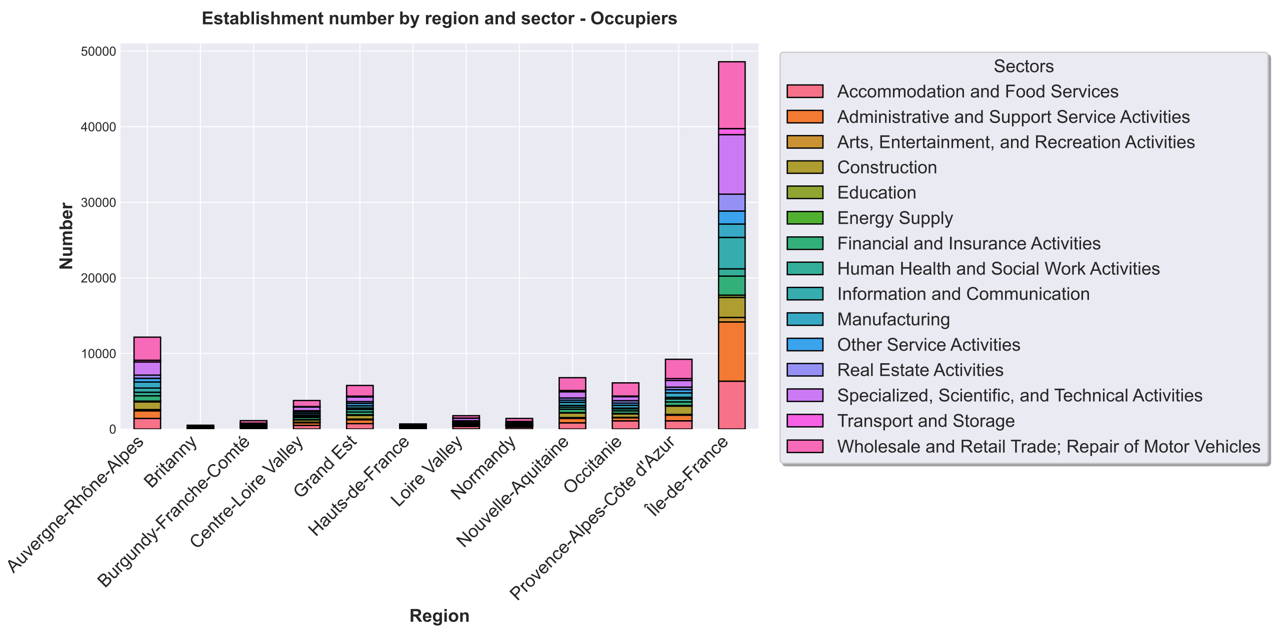


Figure 38: Potential damages for owners - Low return period floods