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Digital twins for bridging climate data gaps: from flood hazards to firms' physical assets to banking risks[1]

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[1] This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Central Bank of the Republic of Türkiye, the BIS, the IFC or the other central banks and institutions represented at the event.

Digital twins for bridging climate data gaps: from flood hazards to firms' physical assets to banking risks

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Abstract

The frequency and severity of floods have increased in recent decades, and this trend is expected to continue due to the long-term rise in temperature, the more extreme weather patterns associated with climate change and the constant degradation of soil quality. Some studies show that floods have a significant and persistent negative effect on company performance (for instance, Fatica et al. (2022)). We complement them by assessing more precisely the location of the floods, distinguishing channels affecting owners and occupiers and connecting the risks faced by firms to the banks that are exposed to them. Combining a series of very granular datasets on flood risks, buildings, establishments, firms and loans, this paper assesses the exposure of banks to physical climate risks through the channel of firms' physical assets. Successive matches are used to obtain for each activity building the associated risk as well as the owner and occupier companies. This helps to disentangle the channels of potential damages that result from flooding. Property damages reduce the owner's equity and increase the Loss Given Default (LGD) associated to the premise while transferable damages (on stocks or productive capital) can affect the income of the user and thus its repayment capacity and Probability of Default (PD). Our application to flood risks in Paris show that losses associated with transferable assets are much bigger than those affecting properties.

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1 Introduction

Physical assets are increasingly exposed to acute climate-related risks like floods and wildfires. This is due to both rising hazards (IPCC, 2021) and the expansion of human activities in vulnerable ar-eas. In the near future, these physical hazards could have significant economic consequences for Non-Financial Corporations (NFCs) and the banks that finance them. Therefore, it is crucial to quantify and analyze the risks posed by climate events to physical assets, necessitating the development of analytical tools to assess both direct and indirect impacts.

Consequently, literature on natural disasters and asset losses is expanding, particularly focusing on flood-related events. This review is not exhaustive but emphasizes business-owned and used assets.

A primary thread of studies highlights the negative impact of hazards on asset prices, especially in residential and, to a lesser extent, commercial real estate (CRE).[1]. Fisher and Rutledge (2021) underline the short-term impacts of major hurricanes on commercial property valuations. They find heterogeneity by building type, as apartment and retail buildings recover faster than other types (office and industrial). In addition to the impact of *realized* disasters on prices, *potential* disasters should also affect prices: some papers show that updating risk perceptions, after observing a storm or learning about newly disclosed flood risk-related information, may induce price discounts. Probably due to data gaps, few studies attempt to quantify the value of the destruction, due to a natural catastrophe, of other types of assets such as machines.

Another strand of the literature derives the link from asset losses to company performances: the literature diverges on this topic. Investigating the impact of a major flood that hit Germany in 2013, Noth and Rehbein (2019) find that firms located in the disaster regions have significantly better economic and financial performance after the flooding, arguing some kind "creative destruction" effect. According to Fatica et al. (2022), this result is driven by the reallocation of capital to non-affected firms in the affected regions. Hence, when using the appropriate granularity, the negative effects of flooding on firm performance may appear more significant and persistent than generally thought. Their study, due to European comparability issues, relies on flood data at the NUTS 3 level and firms geolocation are represented only by their headquarters. Focusing on data at a national level, we complement their analysis by localising the floods risk exposure at the producing premise level.

We further analyze the mechanisms through which firms are 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? Were there indirect effects from infrastructure flooding or disruptions in value chains? These channels are not separately identified, though they likely have distinct consequences, particularly in transmitting economic impacts to the financial system. This issue makes the connection with a last strand of the literature, that studies the impact of hazards on the relationship of affected entities to credit. On the one hand, natural disasters affect the performance of loans. Hurricane Harvey increased housing loans delinquency rates, while flood insurance mitigated some effects (Sweeney et al., 2022). Holtermans et al. (2022) displays convincing evidence that hurricanes Harvey and Sandy had a significant impact on commercial mortgage delinquency rates. On the other hand, the impact of supply of loans remains ambiguous: while earthquake risk reduced the supply of CRE bank loans in California by 2% in the 1990s (Garmaise and Moskowitz, 2009), small banks respond to climate shocks by increasing lending to affected areas and by withdrawing credit from other markets (Cortés and Strahan, 2017). Finally, studies on the impact of hazards on the health of financial institutions are scarce. In Canada, Johnston et al. (2023) find that the direct damages of current and potential floods have small impacts on the financial institutions' Loss Given Default (LGD) on their residential portfolios. They however admit that the lack of granular flood data may have led to an underestimation and smoothing of the risks. In effect, Caloia et al. (2023) consider floods tail risk events in the Netherlands at a more precise granularity and find slightly higher impacts on LGDs and PDs. Part of this higher estimated impact may be due to the fact that the country is partly below sea level, and thus has a relatively high exposure to flood risk.

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

This brief literature review highlights some limitations in existing works, which may affect their ability to fully and accurately assess the direct impact of climate-related hazards on firms' physical assets and their repercussions for the financial system. Three main elements could help making major improvements in that regard:

- 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).
- the definition of physical assets: distinguishing between *transferable* and *real estate* assets enables 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 is made to analyse and assess physical risks to firms.
- the identification of clear transmission mechanisms of climate hazards to the banks that are connected with impacted firms. Property damages reduce the owner's equity and the LGD associated to the premise while transferable damages can affect the income of the user and thus its repayment capacity and PD.

This paper integrates these three key characteristics as part of an international project led by De Nederlandsche Bank (DNB), Hong Kong Monetary Authority (HKMA), and Banque de France (BDF). The goal is to develop a common tool for supervisory authorities using the concept of Digital Twins. Digital Twins are virtual models of physical objects, like buildings, that can simulate shocks such as climate-related hazards. While the paper covers the project's foundation, it primarily focuses on a use case in France, assessing the exposure of buildings to flooding and identifying the users and owners of affected properties.

This paper contributes to several areas of literature. It enhances existing research on assessing physical risks to the economy by integrating highly granular data. It also introduces a new analytical framework linking flood hazards to firms' credit risks, distinguishing between real estate and transferable assets. Most importantly, it provides academics and institutions with an innovative, modular tool that can be easily adapted for assessing climate and nature-related hazards to the economy.

While Section 2 outlines the Digital Twin project and its motivation, Section 3 details the conceptual framework underpinning the French use case. Section 4 provides empirical evidence that supports our hypotheses. Section 5 details the methodology and data we rely on to derive our results displayed in Section 6. Finally, Section 7 provides an overview of the work-in-progress done to connect the Digital Twin to real time risk assessment with the use of satellite data, while Section 8 concludes.

2 The Digital Twins project: Global climate change, localized effects

The motivation underpinning the Digital Twins (DT) project lies in an apparent paradoxical feature of climate change: it is a *global* phenomenon affecting every region of the world but with very *localized* and differentiated consequences depending on many biophysical, social and economic parameters. This peculiarity calls for the development of both generic and very modular tools, in a context where central banks and supervisors still lack the information necessary to account for physical risks in decision-making. Bridging climate-related data gaps through international collaboration, the DT project aims to become a common good open to improvement and to be used widely, especially in countries that do not have the capacity to develop such a tool.

2.1 Project timeline

Phase 1 of the DT project occurred during year 2022 under the impulsion of the Bank of International Settlement Innovation Hub and had two objectives: i) the exploration of potential data sources suited for each institution and ii) the development of the generic architecture of the code. Each of the institutions participating in the project experimented a specific use case adapted to its needs and data resources: for instance, BDF and DNB applied the tool to estimate the impact of floods on real estate, while HKMA performed a similar assessment for typhoons. The structure of the tool is drawn from the hazard-vulnerability-exposure-finance framework commonly used to model catastrophes in the insurance industry. Three modules have thus been developed during Phase 1.

- The **hazard module** models the frequency and intensity of hazards.
- The **exposure module** collects the geographical and physical characteristics of the properties at risk.
- The **vulnerability module** calculates the amount of expected damage to the properties at risk.

The main goal of still ongoing phase 2 was to develop a **financial module** that translates the damage from the vulnerability module into metrics for financial institutions. In that perspective and to maximize the use of AnaCredit the very rich dataset of bank loans to NFCs, the French team decided to focus on the latter.

2.2 Trade-off between global and local data approaches: Evidence from floods

Regarding all the components of risk analysis, the data available at a global level is, most of the time, some sort of lowest common denominator. On the contrary, national data enables:

- Greater accuracy and detail for *hazards* (flood maps)
- Better coverage of *exposures* (location of firms' establishments)
- Tailored methodologies for *vulnerability* (damage functions)

On the other hand, global approach has also some advantages:

- Standardization: consistent definitions, classifications and methodologies, enabling more direct international comparisons.
- Broader perspective: identifying large-scale trends and patterns across regions.
- Efficiency: economies of scale

The Digital Twin bottom-up approach enables to take the best from each country while keeping a general framework, combining global and national approaches:

- Genericity: A common framework to ensure comparability
- Two-steps approach: we can use global datasets as a foundation, but supplement them with national data where available for greater accuracy and detail.
- Transparency: Clear documentation on data sources, methodologies, and limitations.

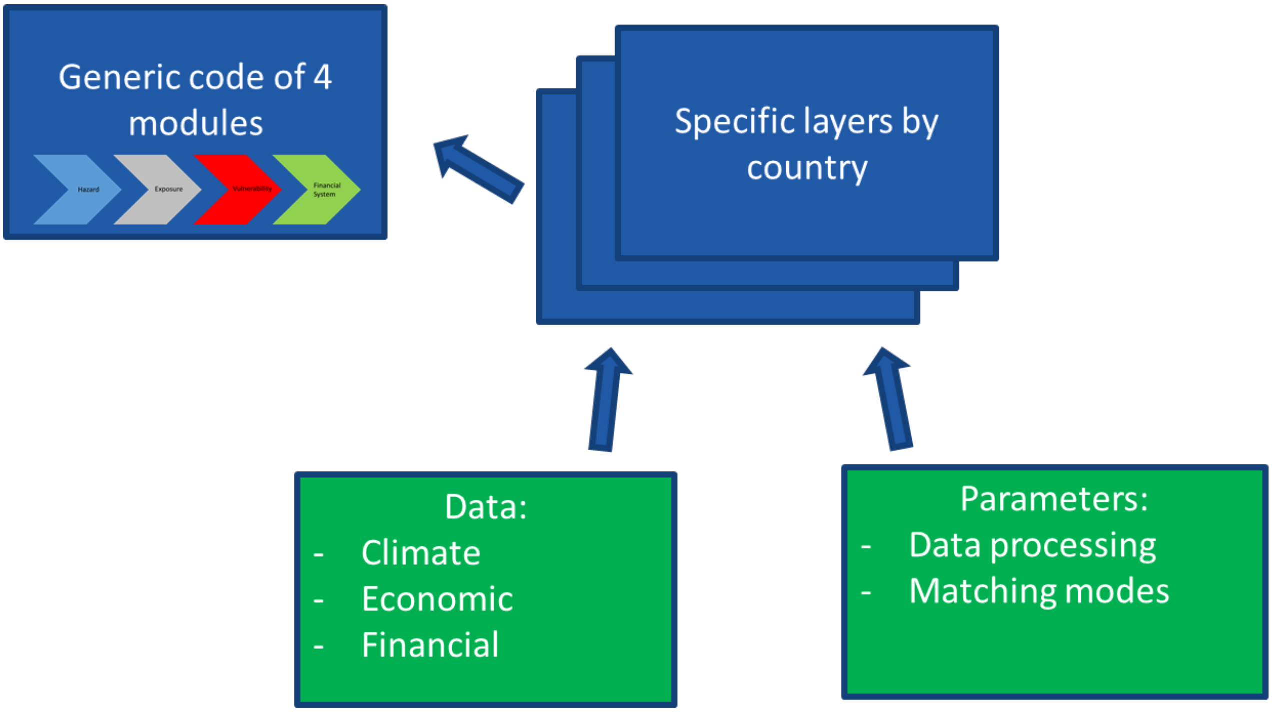
For instance, as we focus our analysis on France, for the hazards module we can use the national official floods maps. These maps provide higher accuracy than modelled maps often used in cross-country analysis (**?**). The recent modeled maps of **?** are available at 100 m resolution and do not account 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.[2] As **?** has shown that protective measures reduce significantly negative flood impact for firms, our official flood data should lead to more realistic results than modeled flood data. The advantages of having modular inputs for exposure and vulnerability are detailed later.

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

2.3 Structure of the tool: generic and flexible

The tool architecture is structured in order to maximize this bottom-up approach enabling to tailor use-cases to the needs and possibilities of each user, while fitting into the common tool.

Figure 1: Owners and occupiers



3 Conceptual Framework: from physical exposure to financial risk

The main objective of this section is to build a systematic framework of analysis to clearly identify the channels through which flood hazards translate into potential damages to firms and then transmit into risks for banks. To do so, we start with a very clear dichotomy: we distinguish buildings from transferable assets that lie inside them. This distinction matters for several reasons. First, 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 (see more below). Moreover, this distinction is also used by insurances and thus the insurance coverage of these two risks can differ across sectors. Last and certainly not least, the entities affected by these two types of damage differ most of the time: while CRE increasingly became a financial asset, the user of a a premise in a building is not necessarily the owner of this premise. In these cases, and they are many, transferable and real estate assets do not belong to the same entity.

3.1 Two types of direct flood-induced damages

Two direct damage channels are identified:

- *Property* damage: a drop in the value of the affected building or the necessity to pay repair costs;

- *Transferable* damage: 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. Computing a granular exposure to such a risk and its potential impact seems complicated. Thus, we decided not to not take them into account.

3.2 Who is affected by what type of damages?

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

When a building is flooded, its owner will face property damages reducing his asset, while transferable damages apply to the user's assets. Firms using the building they own (or when the user and owner firms belong to the same entity) face both property and transferable damages.

We develop a four-step strategy to account for these damages and link them to credit risk:

- Geographical matching of buildings and hazards
- Matching of buildings and establishments
- Computation of damages (asset losses)
- Connecting to the banking system

Sketch 2 is built as a decision tree that tries to sum up this whole framework up, namely both the conceptual framework deriving the transmission from climate hazards to credit risk metrics and at the bottom the successive methodological steps. We first match flood hazards data with buildings 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 matchings (one matching for owners and for users). We then compute for each hazard/building/firm the associated damages. Finally, we connect the losses to banks and specific credit risk metrics. Transferable damages impair the productive capacity and the income of firms and can thus reduce their repayment capacity and probability of defaults (PD). Property damages decrease the value of the premise. While a significant share of NFC loans are collateralized by a real estate property, a drop in the value of this property increases the loan LGD, i.e. the value that the lender will not receive in case of default of the creditor.

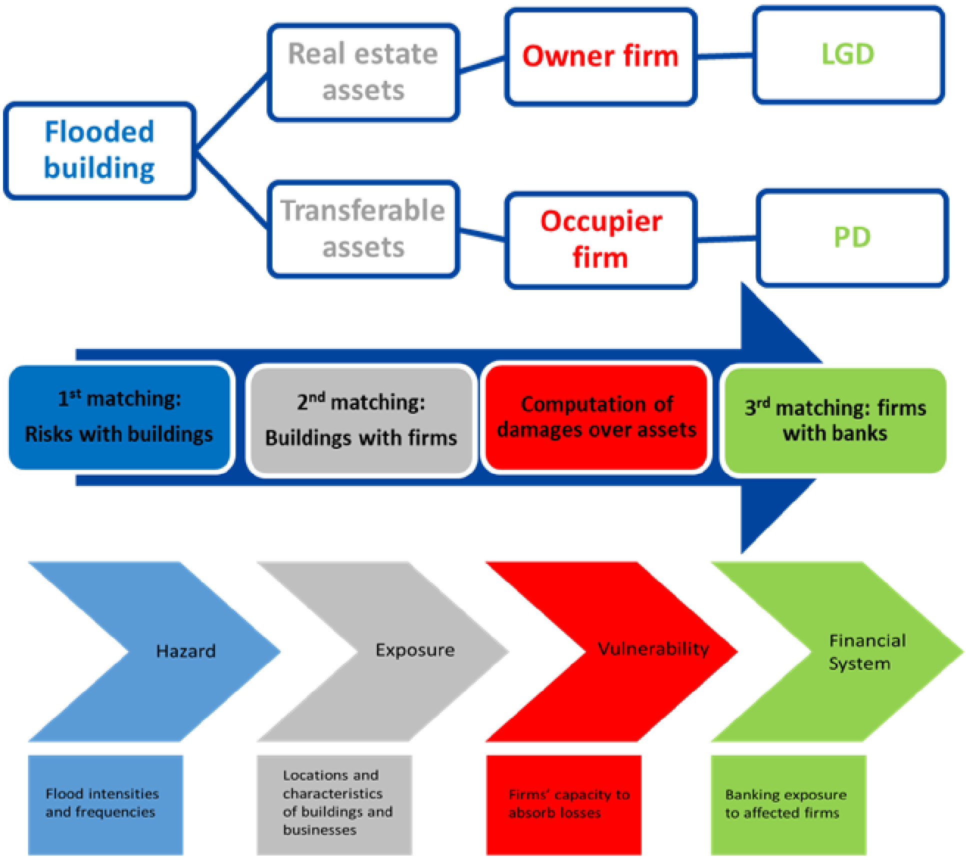
3.3 Motivation: Effect of past floods on owner and occupier firms

Using historical data on floods, we show that owners and occupiers are affected differently through their real estate and technical installation. Based on this observation, the core of our paper builds a framework distinguishing channels for owners and occupiers to evaluate the effect of different floods scenarios on NFCs' assets and the exposure of banks to these NFCs.

We use French NFCs balance sheet data (Fiben) to determine which are owners and which are occupiers. NFCs having a positive amount of real estate assets are considered owners, while the others are considered users.[3]

[3]This selection method identifies only renters as users, and does not enable to select owner-occupiers.

Figure 2: Sketching summary



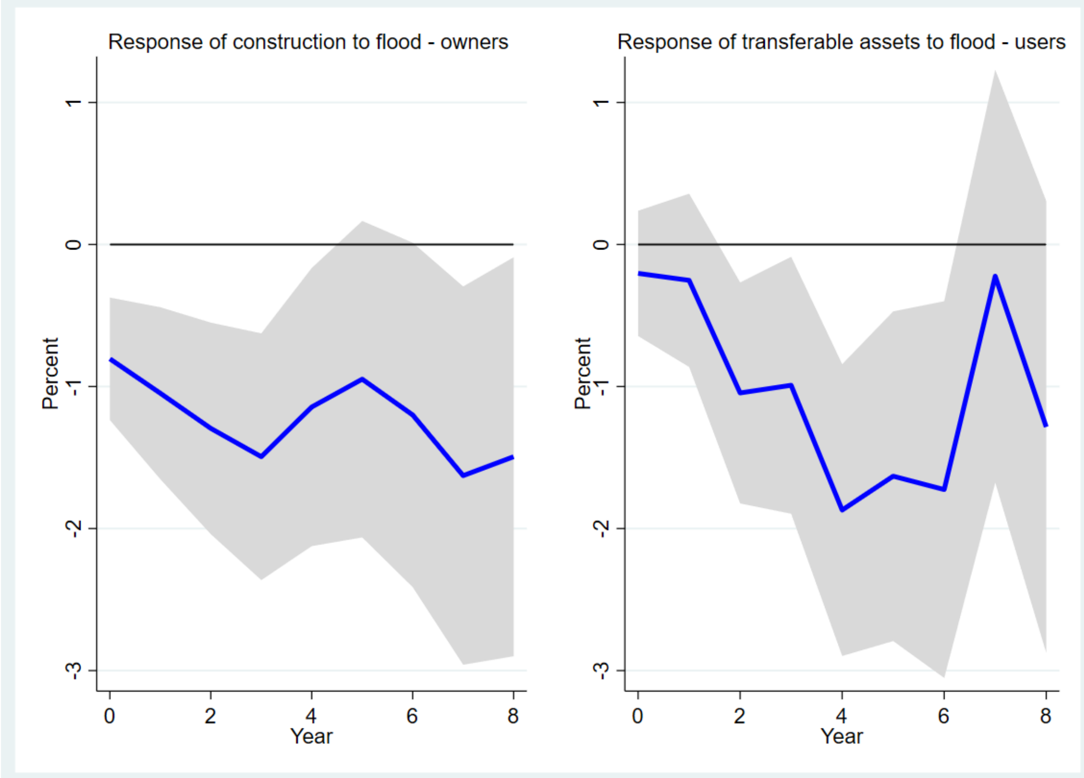
We first present the main linear regressions, where we regress respectively real estate capital and transferable capital on city affected on flood shocks at the city level. We use French NFCs balance sheet data (Fiben) and location of historical floods according to the CatNat data. We consider a NFCs is affected by a flood at time t is the postal code in which it is localised is affected. We use local projection methods (Jorda, 2005), which involves running separate regressions for each horizon h = 0,...,6 years :

$$log(y_{i,t+h}) - log(y_{i,t+h-1}) = \beta_h F_{i,t} + \gamma_h X_{i,k<t-1} + \mu_i^h + \zeta_i^h + \epsilon_{i,t+h} \quad (1)$$

where the dependent variable is the cumulative percentage change in the logarithm of the real estate and transferable capital from period t to $t+h$ for firm i. $F_{i,t}$ is a binary variable indicating whether the city where the firm is located has been affected by a flood at time t. The vector of firm specific variables $X_{i,k<t-1}$ includes the number of employees, the sector and localisation at the NUTS 3 level of the firm. Thus, we control for economic shock occurring at NUTS-3 level and on a specific sector. Fixed effects μ_i^h control for the time invariant idiosyncratic firm characteristics and time fixed effects ζ_i^h account for unobserved aggregate shocks[4].

[4]We only select single establishment in the sample

Figure 3: Effect on real estate and transferable assets



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

Figure 3 confirms our hypothesis about differentiated impact of floods on owners and users. The left-hand side chart shows the effect on the value of real estate assets for owners. For these NFCs, being located in a city affected by a flood has a negative impact on the value of their real estate assets. Regarding transferable assets, while we do not find any negative impact of floods if we use the full sample of NFCs, we find one when restricting the scope to occupiers only (right hand side chart). Interestingly, even if firms should benefit from some insurance framework, we observe a significant impact on assets.

4 Data and Methodology

4.1 Comprehensive and granular datasets

The use-case has been tailored to maximize the use of the very comprehensive and granular datasets that are available in France. In order to favour the adoption of our tool and encourage its distribution to as much as possible, we used some open data sources for the measurement of exposure of physical assets to floods. The subsequent analyses rely on unique datasets on firms balance sheets and credits, provided by Banque de France and the Eurosystem.

4.1.1 Data on buildings

The BNDB (Base de Données Nationale des Bâtiments, National Buildings Database) is a mapping of the existing building stock. 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 geospatial intersection of around twenty databases from public organizations. 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.

4.1.2 Data on flood hazards

The data on flood hazards we use are static data that consists of the zoning 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 characterized by a certain level of risk (high, medium and low probability of occurrence corresponding to *circa* 10, 100 and 1000 years period returns). The fact that TRI focus 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. Floods' scenarios are respectively :

- High frequency: An event causing the first significant damages, with a return period between 10 and 30 years.
- Medium frequency: 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 frequency: 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.

4.1.3 Data on firms and establishments

All French firms are characterized by a SIREN, a number. Establishments are firms' producing premises which are located in buildings. Produced by Insee, the Sirene database (Répertoire National d'identification des entreprises et des établissements) provides information on each business establishment located in France. It includes all the companies in activity when the database was created in 1973 and those created since then.[5] We use the dataset called StockEtablissementHistorique, including historical data on the establishments (each with an identifier called SIRET) of each company (each with an identifier called SIREN) in France. The variables of interest for us are the opening and closing dates of the establishment, its economic sector (NAF code or NAP code before 1993) and whether the establishment is hiring workers. We obtain the geolocation of each establishment thanks to a merge of this dataset with the "Géolocalisation des établissements du répertoire Sirene" dataset,[6] based on the SIRET identifier.

4.1.4 Data on loans

AnaCredit is a dataset of the European Central Bank, containing detailed information on individual bank loans in the euro area, harmonized across all member states, with data collection starting in 2018.

4.1.5 Data on historical 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.

4.2 From hazards to exposure: a succession of matchings

4.2.1 First matching: hazards and buildings

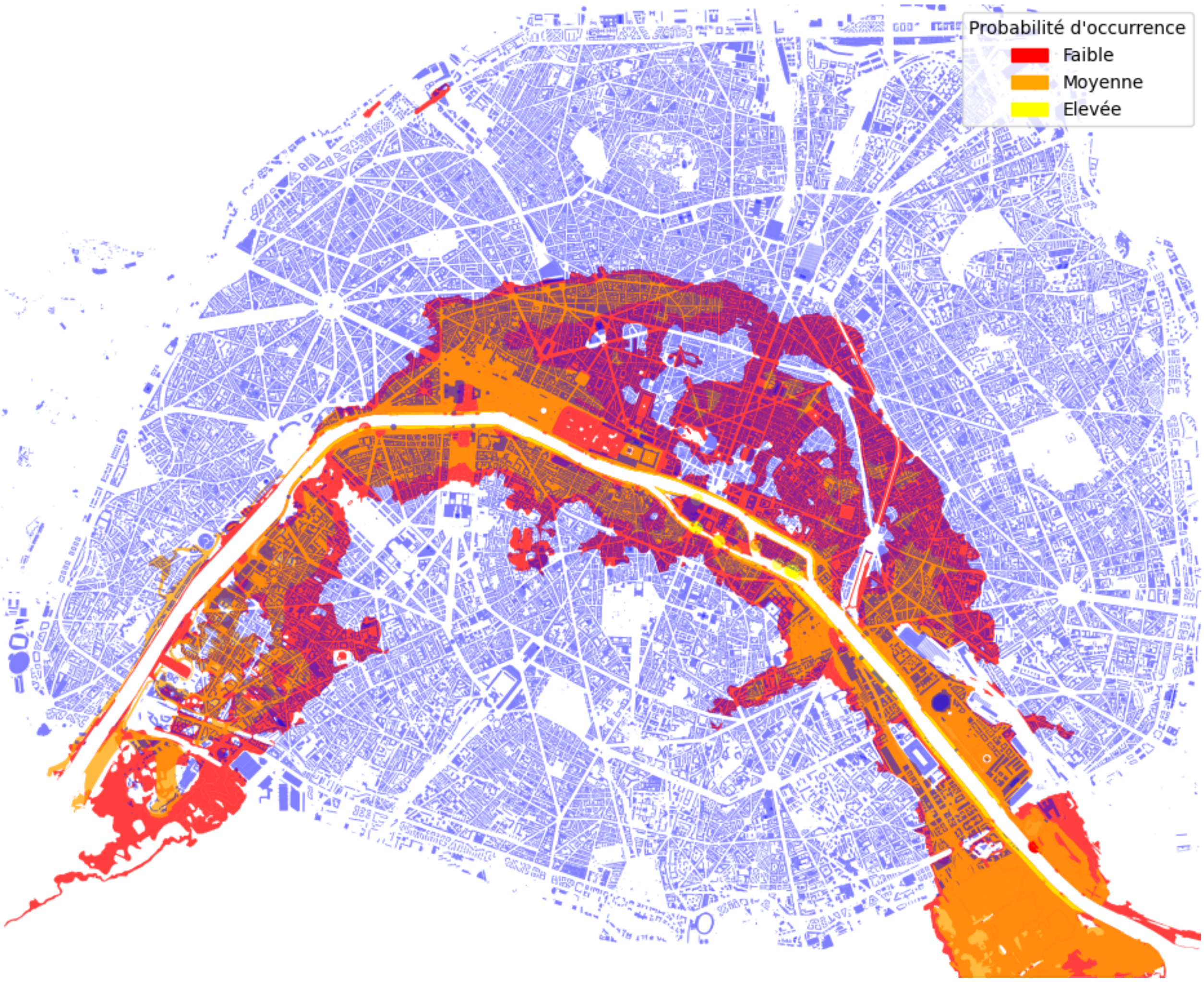
This matching aims at getting information on the exposure of buildings to flood risks. For that, we compute the spatial intersection between the BNDB and the TRI at the building level: for each

[5] Public administrations were included in 1983, and farms in 1993.

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

French activity building, we obtain the flood hazards it is exposed to, according to three scenarios (high, medium and low occurrence probability). Figure 4 displays the buildings and the probability of flood occurrence. As a building can lie on several polygons of hazard, we keep only the polygon whose overlap area with the building is the largest.

Figure 4: Hazards and buildings



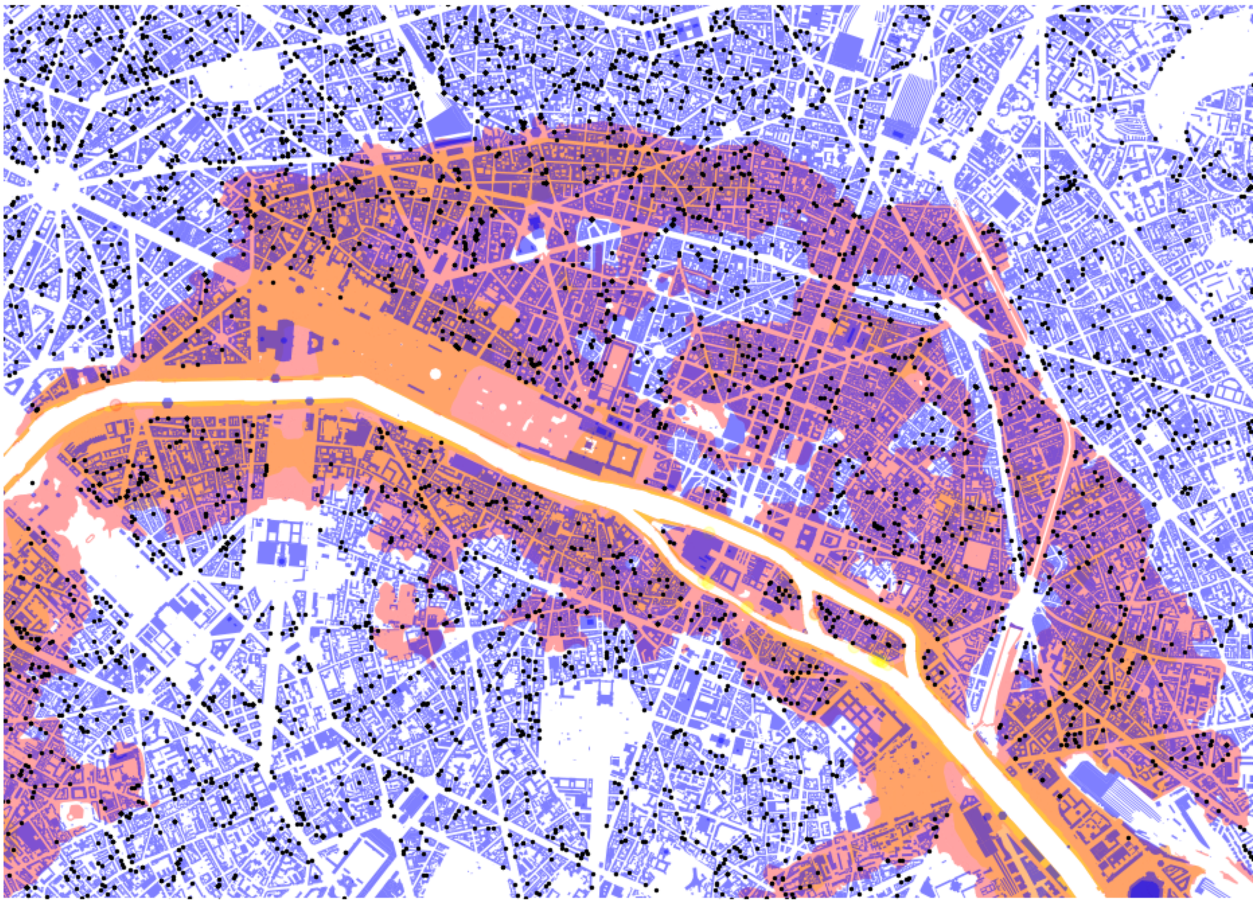
4.2.2 Second matching: buildings and firms

The idea of this second matching is to connect the threatened buildings to the entities that might suffer from the materialization of the risks. As explained above in the Framework section, this materialization can occur through distinct channels: damages to the building itself affect its owner, while damages to the physical capital *inside the building* will impact the firm that uses the building to produce, store its inventories or operate its business. We thus implement two different matchings, connecting buildings with their owner on one side and their user on the other.

Owners: Most of activity buildings do not belong to the firm that uses them. French data on CRE transactions show that about half of the volume is bought by investors. The BNDB displays for each building information on its owner: when it is owned by a legal entity (firms, most of the time), it is associated to a SIREN identifier. This very precious information thus enables us to identify the owners of exposed buildings, but also to compute some statistics on them.

Occupiers: We follow a method 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. We match each point representing an establishment (SIRENE database) to the nearest polygon representing an exposed building through a nearest-neighbour spatial joint. Figure 5 helps vizualising this spatial matching. Hence, while one establishment can only be matched with one building, multiple establishments can happen to be in the same building. 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, SCI and whose physical footprint, hence their exposure, is limited.

Figure 5: Buildings and Production sites



4.3 Computation of sector-varying transferable and real estate damages

When developing flood damage functions for firms, INRAE explicitly distinguished between real estate and transferable damages. As a very salient and interesting feature, they vary with the sector of the firm that is affected: for instance, the damage on transferable assets in the building occupied by an insurance company are much lower than those in a battery factory. For other parameters, these functions take the severity of the flood (height) and two specific variable accounting for the size of the asset loss: the size of the building in m^2 for property damages and the size of the firm in terms of employees for transferable damages. We then apply these functions to the pool of firms according to the dichotomy explained earlier: transferable function for users and property function for owners. These are the asset losses that will be hereafter used.

4.4 Discussion of the methodology: Some specific issues and limitations

4.4.1 What about insurances?

Insurances play a mitigating role in transferring losses out of the direct transmission from firms to banks. While we do not have the adequate data to account for them, our conceptual framework and estimates remain relevant to understand what would happen without insurances, in a context of growing concerns around insurance coverage gaps and inassurability in some sectors or areas.

4.4.2 What about floors?

Since the BNDB is at the building level and since the geolocation of the establishments is in two dimensions, our information remain at the building level. Thus we are not able to directly tell whether the owner or the user of a premise is really 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 as compared to office activities (example?). While the latter are hosted in buildings with multiple floors, industrial or commercial activities tend to locate in 1 floor buildings (see [de L'Estoile and Salin (2024)]). Thus, the sectors that will face important damages should be the ones for which the issue of floor is less relevant.

4.4.3 Matching with Users: Why using buildings?

One major point of the methodology is the reliance on an intermediary object between hazards and firms: the building. Whereas a 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 do not account for its real physical exposure. The building step enables to give establishments back their real land footprint.

5 Stylized facts in Paris: From physical exposure to financial risks

This section sums up the results obtained by applying this methodology to the territory of Paris. This choice was made according to several reasons related both to high vulnerability and hazards:

1. it represents high economic and social stakes both in terms of physical assets and outstandings for banks

2. Paris' riverside location within a natural floodplain, its connection to major tributaries, tidal influences, and the narrow river channel all contribute to making the city highly susceptible to devastating floods originating from the Seine River

3. ageing infrastructure: Much of Paris' drainage and sewage infrastructure was built in the 19th century and is vulnerable to being overwhelmed during major flood events

4. the last 100 years return period flood dates back from 115 years, the catastrophic 1910 "Great Flood" where the Seine rose over 8 meters above normal levels.

Our results are split along the distinction we draw between users and owners. We start by displaying some metrics on the exposure of firms, especially by comparing the potential losses they face as compared to the assets they own. We then show that the banking system is rather exposed to threatened firms, and that these risks can be concentrated. Finally, we look at relevant credit risk metrics: PDs for users and LGDs for owners.

5.1 Metrics on the exposure of firms

A first salient feature is that many buildings and thus many firms are exposed to middle to low flood hazards in Paris. Specifically, we find that around 18406 buildings, 34000 user firms and 27000 owning firms could be hit by a flood with a low probability of occurrence.This unpredictable risk with extreme consequences is exactly the kind of "green swan" for which central banks and financial regulators need tools to understand, prepare for, and mitigate the impacts. Therefore, we will focus on this scenario for the remainder of the paper.

5.1.1 Metrics on the exposure of firms: users

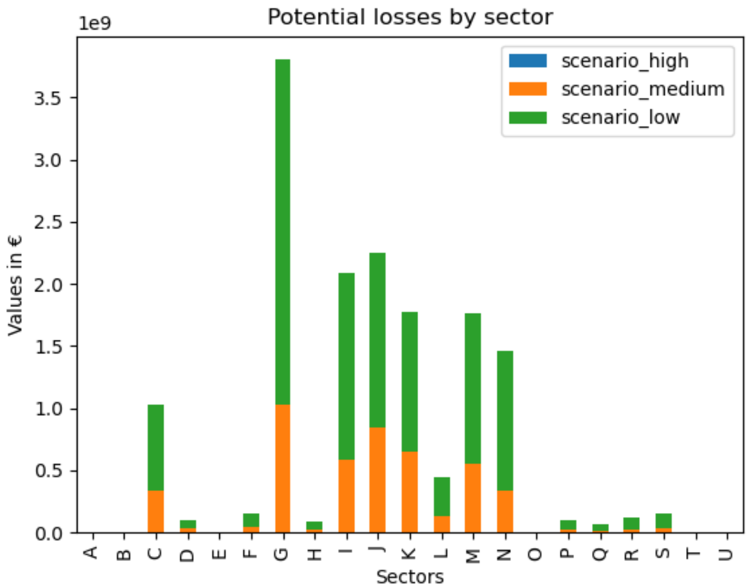
Table 2 displays some descriptive statistics regarding the exposure of user firms to flood hazards. As expected, the gravity of flooding grows when its probability of occurrence decreases. The worst case scenario estimates a 10 bns € losses in productive assets.

Table 2: Descriptive Statistics for User Firms by Scenario

Scenario	High	Medium	Low
Number of exposed firms	8	15656	33852
Damages in bns €	0.07	4.6	10

These losses are unequally distributed among sectors, as shows Figure 6. Retail and Gross Trade firms are the most affected (Sector G) with 3.6 bns € in the worst case scenario, mainly because a large share of affected firms are from this sector (30%). Interestingly, Manufacturing (Sector C), which represents only 5% of impacted firms, exhibits large losses because of the weight given by the damage function to manufacturing productive capital.

Figure 6: Potential losses by sector - User firms



In order to assess the vulnerability of user firms, we weight their losses by their total assets, computing their Losses on Assets ratio (LoA). In the following results, we define a firm as highly damaged when its LoA exceeds 10% (a threshold represented by the vertical red line in the following graphs). It it interesting to look at the characteristics of the most affected firms. Figure 7 shows that small firms (Petites et Moyennes Entreprises, PMEs) are likely to suffer the most as their assets are low. However, a number of intermediary firms (Etablissements de Taille Intermédiaire, ETI) could lose more than 20% of their assets. Figure 8 indicates that in two sectors, half of the firms could be highly damaged (Manufacturing (C) and Accommodation and Food Services (I)).

Figure 7: Potential losses on assets by size - User firms

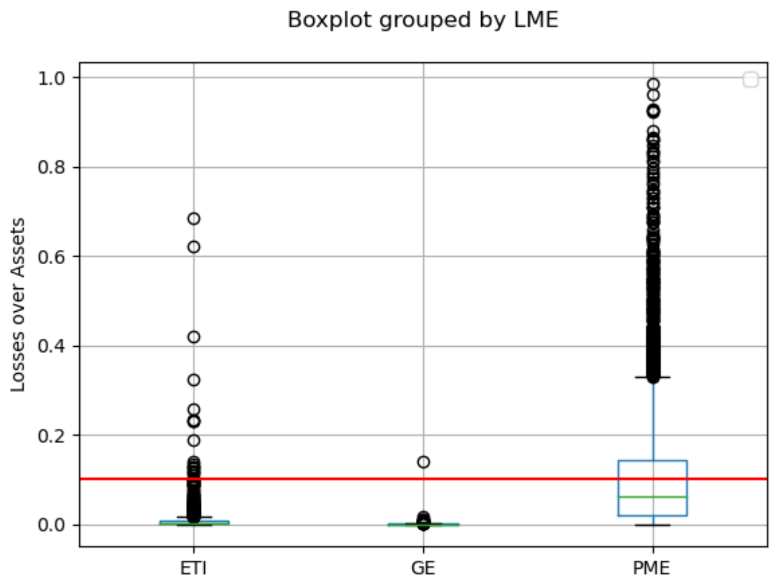
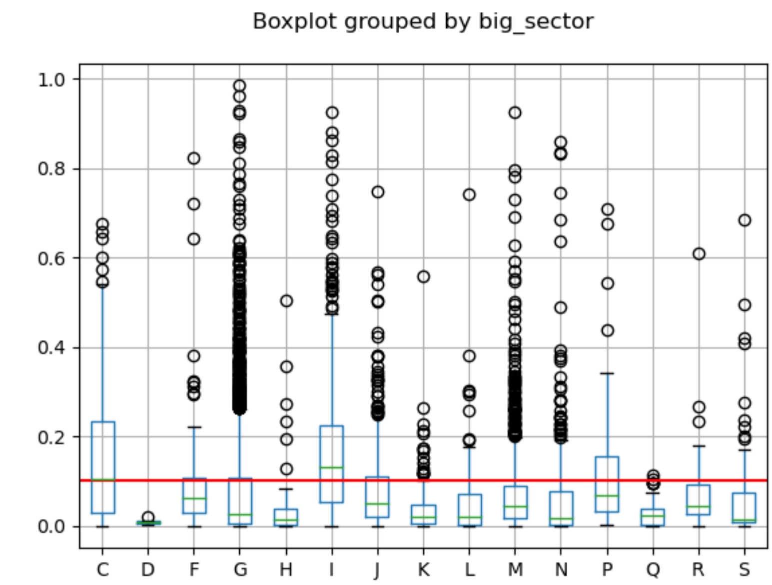


Figure 8: Potential losses on assets by sector - User firms

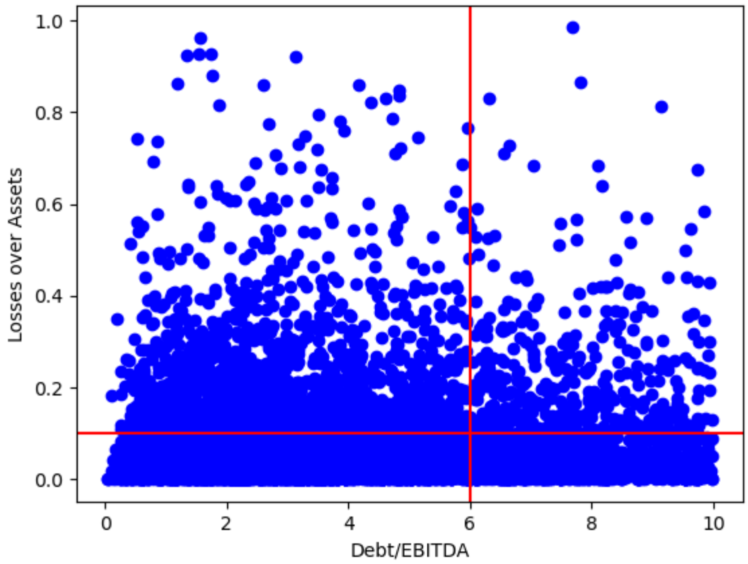


Finally, it is valuable to cross-reference these findings with additional information on firms' indebtedness-coming from the Fiben database[7]. Firms whose Debt/EBITDA ratio exceeds 6, a commonly used threshold to assess indebtedness (represented by the vertical red line in the following graph) are considered highly indebted. According to Figure 9, a significant amount of firms, at the upper-right of

[7]By merging our dataset with Fiben, we lose 30% of our sample of firms whose annual turnover is lower than 750000€

the crossing lines, are both highly affected and very indebted, and thus represent a risk for the banks that are exposed to them. The exposure of banks to these risks are studied later.

Figure 9: Potential losses on assets vs Debt/EBITDA - User firms



5.1.2 Metrics on the exposure of firms: owners

Table 3 shows that, whereas the number of exposed owning firms is rather comparable to the number of user firms, their losses are much lower. This comes from the parameters of the damage functions where damages are much higher for transferable assets than for properties.

Table 3: Descriptive Statistics for Owner Firms by Scenario

Scenario	High	Medium	Low
Number of exposed firms	8	12400	26852
Damages in bns €	0.0003	0.05	0.2
Exposed surface in mns of m^2	0.001	1.1	2.2

These losses are mostly supported by real estate firms, but a significant share of them could be Sociétés Civiles Immobilières (SCI), a common type of firm in France that are often be 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.

5.2 Metrics on the exposure of banks

To assess the exposure of French banks to the highly threatened NFCs detailed above, we use the AnaCredit dataset.[8]

5.2.1 Metrics on the exposure of banks: users

The outstanding associated to highly vulnerable firms are relatively high as shown in Table 4. As

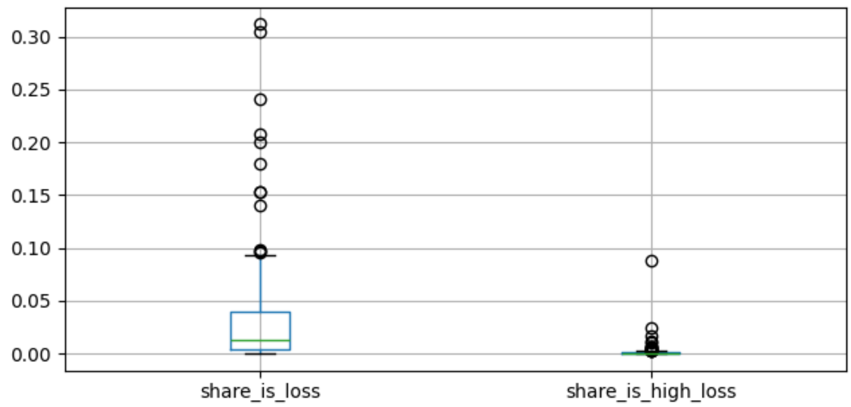
[8]The matching generates some losses in our firms samples (30% for users and 20% for owners)

Table 4: Descriptive Statistics for Exposure of Banks to User Firms (Low Scenario)

Statistic	Number	Outstanding in bns €
User	20644	4
User with heavy losses	6021	1.7
User with heavy losses and debt	2540	1

compared to the amount of lending of French banks to NFCs (around 1200 bns €), these figures remain quite low. But some medium banks have a significant share of their lending portfolios that are exposed to vulnerable firms : more than a quarter of French banks have more than 0.5% of their total lending to NFCs that is exposed to damaged NFCs (Figure 10).

Figure 10: Potential losses on assets by banks - User firms



5.2.2 Metrics on the exposure of firms: owners

While the majority of owner firms do not face a high LoA because of the high value of property assets, half of those that could be highly affected are also highly indebted (Table 5). This is due to the structural high leverage of real estate firms ().

5.2.3 Metrics on the exposure of banks: owners

Table 5: Descriptive Statistics for Exposure of Banks to Owner Firms (Low Scenario)

Statistic	Number	Outstanding in bns €
Owners	20216	0.2
Owners with heavy losses	2021	0.02
Owners with heavy losses and debt	1050	0.01

5.3 Credit risk metrics

5.3.1 Credit risk metrics for owners: LGDs

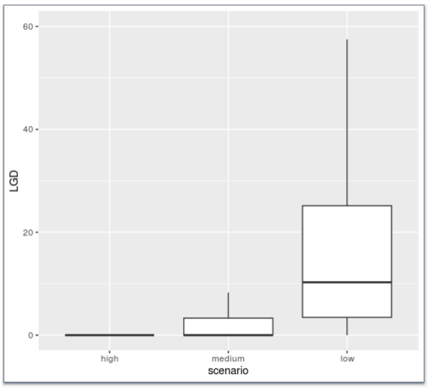
Loss given defaults (LGDs) are not reported in AnaCredit. Hence, we approximate loan-level LGDs by looking at the collateral value relative to the notional value of the loan. This is predicated on the assumption that, in the event of a default, a bank can only recover the collateral assigned to the loan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

$$\text{LGD}_S^i = \max\left(0, \frac{L^i - C_S^i}{L^i}\right) \tag{2}$$

with L_i the outstanding amount of the loan and C_S^i 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.

Figure 11 shows that the median increase in LGD after the flood impact would reach around 10 basis points in the low probability of occurrence scenario. This result gives the same order of magnitude as Caloia et al. (2023).

Figure 11: Effects on LGD (basis points), by scenario



5.3.2 Credit risk metrics for owners: PDs

We also follow a stress test approach to assess the potential effect of floods on users' PD. To that end, micro-founded models are used using AnaCredit data. We estimate and project the PD for each sector separately. Even if the firm is only a user of the building, we project that the reduction of collateral increases the leverage as the debt is higher relative to assets the firm can use if the equipment inside is affected by the flood.

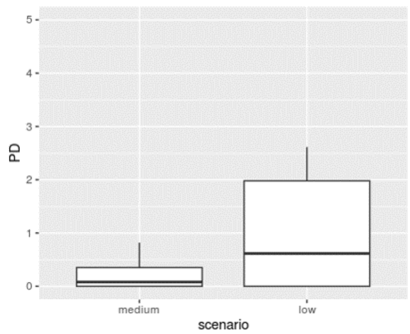
$$PD_t^i = \alpha + \beta_1 \text{leverage}_t^i + \beta_2 \text{asset turnover}_t^i + \epsilon_t^i$$

Where:

- leverage_t^i is total bank debt/total assets for scenario s and firm i
- $\text{asset turnover}_t^i$ is total sales/total assets for scenario s and firm i
- the dependent variable $\text{PD}_t^{i,s}$ is the average probability of default declared by banks for the counterparty i at time t. We estimate the model at half-yearly frequency as firms' annual account can be updated half-yearly

We project the probability of default (PD) using projected total asset values, which are reduced based on estimated damages from different scenarios. As in Emambakhsh et al. (2023), we estimate and project PD separately for each sector using the model. Figure 11 shows the distribution of PD effects by scenario. The impact remains small, as we only consider the asset channel. The hypothesis is that equipment destruction lowers total assets and firms' production capabilities. However, other significant channels, such as productivity loss following an adverse event like a flood, could also play a role.

Figure 12: Effects on PD (basis points), by scenario



6 Completing the Digital Twin: Towards real time risk assessment through the use of satellite data

To fully comply to the concept of a Digital Twin, we - together with the DNB team - have put a strong emphasis on developing the possibility to follow flood catastrophes and their near real-time impacts on firms and banks. To that end, we thoroughly worked on the interoperability between the tool and satellite data. We relied on the Global Floods Project[9], which provides free access to data from the European Copernicus Sentinel 1 satellite. This satellite provides radar imagery, which is relevant for observations of flooded areas. The site offers the possibility of using a REST API, which can be used to obtain images via various end points. The processes described below are written in Python.

The concepts to be familiar with are those of *zones of interest* and *products*. A *zone of interest* is the geographical area that needs to be monitored. A *product* is a set of data relating to flooded areas, stored as a set of files in a compressed archive. Within a product, different layers are displayed to describe flooding based on various criteria, including the extent of flood.

This element has been used to study the important floods that occurred in the North of France Pas-de-Calais region in November 2023. The process is as follows: we start by querying the area of interest for the period in question and obtain different *products* for each day of the period. We then retrieve files in GeoJSON format containing the geographic data corresponding to the flooded data.

Depending on the satellite trajectory, each *product* file corresponds only to a part of the area of interest. We thus merge all the areas provided over the period into a single one. Across this process, we check that the zone thus defined completely covers the area of interest to make sure we get all the flooded areas during the period. While this methodology is based on two-dimension representation and does not enable to account for the depth of floods, strong improvements are being made in that way.

This alternative flooding data is currently being implemented in the tool, so that it can be used as the hazard layer in replacement of the TRI data set. While this add-on to the tool enables to compute potential damages at a near-real-time frequency, it also demonstrates the modularity of the tool. It is thus emblematic of the deflating entry cost to the project.

7 Conclusion and avenues for future developments

This work relies on three main innovations: integration of very granular datasets, distinction between property and transferable assets and the identification of clear transmission mechanisms of climate hazards to banks *via* firms. We find that a high share of Parisian buildings and firms (owners and users) are exposed to flood hazards. These could turn into significant losses for firms, that may seriously impair firms' assets, especially for those which are highly indebted. Finally, our findings show that losses associated with transferable assets are much bigger than those affecting properties.

[9]

In that sense, contents matter more than containers. However, the risks associated to a decrease in the value of impacted collateral is not neglectable. It is important to bear in mind that the hazard data we use for the moment reflects flood probabilities of occurrence based on past data. The planned incorporation of projection data would certainly worsen the picture.

This methodological work opens the floodgates to numerous subsequent analyses. While there are already extremely rich information to derive from descriptive statistics, more analytical questions could be answered. For instance, our setup enables to study the evolution of credit distribution patterns in connection with flooding events. Finally, the Digital Twin project from which this work emanates is set to improve in the near future across two directions: *deepening*, with an improvement of existing use-cases; and *enlargement*, with the integration of other types of risks (wildfires, drought etc.) and other participants.

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