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(Markets, Infrastructures, Payment Systems)

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the Italian firms' physical risk-adjusted probability of default

by Manuel Cugliari, Simone Narizzano and Federica Vassalli



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The papers published in the 'Markets, Infrastructures, Payment Systems' series provide information and analysis on aspects regarding the institutional duties of the Bank of Italy in relation to the monitoring of financial markets and payment systems and the development and management of the corresponding infrastructures in order to foster a better understanding of these issues and stimulate discussion among institutions, economic actors and citizens.

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HYDROGEOLOGICAL AND CREDIT RISK: THE ITALIAN FIRMS' PHYSICAL RISK-ADJUSTED PROBABILITY OF DEFAULT

Manuel Cugliari*, Simone Narizzano*, Federica Vassalli*

Abstract

We assess the impact of climate-related physical risks on the one-year probability of default (PD) of Italian non-financial firms, focusing on hydrogeological risks such as floods and landslides. We compile a dataset combining firms' financial data with the geographic location of their operational units, matched to hazard levels. We derive for each firm: i) a discrete risk indicator; ii) a PD adjusted for hydrogeological risks, calculated by rewriting the financial statement items so as to incorporate the expected loss due to hydrogeological risk. Our analysis shows that 38 per cent of firms are exposed to hydrogeological risks, with notable regional and sectoral differences. On average, exposure leads to a small increase in PD and limited economic impact, with negligible effects on collateral used in monetary policy operations. However, firms in high-risk areas suffer a higher drop in creditworthiness. Insurance coverage mitigates this effect across the entire sample, reducing the PD impact by half on average. These findings reflect current conditions. The expected increase in the frequency and severity of extreme events in the near future could amplify the negative effects on firms' credit profiles.

JEL Classification: C14, C55, G24, G32, Q54.

Keywords: credit risk, physical risk, probability of default, hydrogeological risk.

Sintesi

Il lavoro valuta l'effetto dei rischi fisici legati al cambiamento climatico sulla probabilità di insolvenza (PI) a un anno delle imprese non finanziarie italiane, concentrandosi sui rischi idrogeologici come alluvioni e frane. Il dataset utilizzato integra dati finanziari aziendali con la localizzazione geografica delle unità operative, corredata dal relativo livello di rischio idrogeologico. Si calcola, quindi, per ciascuna impresa: i) un indicatore di rischio discreto; ii) una PI aggiustata per i rischi idrogeologici, ottenuta riscrivendo le poste di bilancio in modo da integrare la perdita attesa associata ai rischi idrogeologici. L'analisi mostra che il 38 per cento delle imprese è esposto a rischi idrogeologici, con forti differenze regionali e settoriali. In media, l'esposizione comporta un lieve aumento della PI ed effetti economici contenuti, con risvolti trascurabili sulle garanzie utilizzate nelle operazioni di politica monetaria. Tuttavia, il deterioramento della solidità creditizia è maggiore per le imprese in aree ad alto rischio. La copertura assicurativa attenua l'effetto per l'intero campione, dimezzando in media l'impatto sulla PI. Un eventuale aumento della frequenza e della gravità degli eventi estremi nel futuro porterebbe, presumibilmente, a un aggravamento degli effetti del rischio idrogeologico sul merito creditizio delle imprese.

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CONTENTS

1. Introduction	7
2. Modelling hydrogeological risk	10
2.1 Flood	10
2.2 Landslides	11
3. Data	12
3.1 Hazard - ISPRA	12
3.2 Exposure - Infocamere and Cebi/Cerved	14
3.3 The S – ICAS model	16
4. Methodology	17
4.1 Geo-referencing local units	17
4.2 Risk-adjusted firms' financial statement	22
5. Results	27
5.1 Discrete indicators	27
5.2 Physical-Risk Adjusted PD	31
6. Further results	38
6.1 The impact on collateral in monetary policy operations	38
6.2 Does insurance matter?	40
7. Conclusion	41
Appendix A	ii
Appendix B	iii
Appendix C	iv
Appendix D	vi
Robustness checks – OpenStreetMap geolocalisation	vi
Robustness checks – Alternative hazard probability	xii
Robustness checks – Alternative flood vulnerability measure	xiv
Robustness checks – Single branch firms	xvi

1. Introduction¹

Climate change is reshaping the natural environment and catalysing more frequent and intense natural disasters. These events have significant economic and business consequences, that may affect firms' soundness. Natural hazards can result in the destruction of tangible assets and prolonged operational disruption, potentially leading to insolvency (Monnin, 2018). However, assessing physical risks remains challenging, as the most severe events, such as floods and landslides, are typically localised. At the same time, precise data on the geographic distribution of firms' assets are often unavailable.

In Italy, the increasing frequency and severity of floods and landslides (collectively referred to as hydrogeological events, or HG) cause considerable damage and pose significant threats to the population (Guzzetti and Reichenbach, 1994; Guzzetti and Tonelli, 2004; Gatto, *et al.*, 2023). The Italian Agency for Environmental Protection and Research (ISPRA) annual report reveals that 7,423 Italian municipalities (93.9 per cent) are at risk for landslides, floods, or coastal erosion. Industries and services located in high and very high landslide hazard areas are over 84,000, with 220,000 employees exposed to risk. Additionally, in a medium-risk flood scenario, over 640,000 employees (13.4 per cent of the total) are exposed to flooding risk. Flooding is particularly notable for its economic devastation (Barredo, 2009; Bower *et al.*, 2010; Luger *et al.*, 2010; Barredo *et al.*, 2012) and it is Europe's most significant natural risk (Arrighi *et al.*, 2018). In Europe, the expected annual loss by 2100 due to flood amounts to €44 billion, which could be substantially reduced by detention areas (Dottori *et al.*, 2023). Notably, insurance coverage for asset damage caused by natural disasters, including HG risks, has recently been made mandatory in Italy (Law 213/2023), though its implementation is still pending.

The growing regulatory attention and the rising frequency of extreme event have heightened firms' awareness of climate-related risk. In 2014, only 7 per cent of Italian firms consider natural and climate risk as highly relevant (Salvati *et al.*, 2014), whereas by 2022 this proportion had increased to 73 per cent (Gallo *et al.*, 2022). Also, non-financial firms affected by HG events are 7.3 per cent more likely to exit the market than unaffected firms. In fact, physical risk can negatively impact cash flows through several channels, such as production disruption, both due to direct damages, work absenteeism or supply chain interruptions, lower sales (e.g. demand shock in the affected area) and increase in capital costs for restoring damaged assets (Monnin, 2018). These firms also experience an average decline of 4.9 per cent in revenue and of 2.3 per cent in employees (Clò *et al.*, 2024).

Thus, it is crucial to understand the extent to which Italian firms are exposed to HG risk and how this impacts their creditworthiness and the possible side effects, such as limited access to credit and reduction in collateral value that underpin credit (Monnin, 2018). Between 2012 and 2016, 5.3 per cent of firms in

¹ We are grateful to Gioia Cellai, Francesco Columba, Paolo Del Giovane, Francesco Monterisi, Tommaso Perez and Antonio Scalia for their useful comments. We also thank Stefano Di Virgilio and Paolo Parlamento for their contribution in the development of the dataset and in the analysis of the firm's financial statement from the perspective of climate risk.

Italy experienced losses or incurred expenses to restore their businesses following floods or landslides, subsequently facing difficulty in the access to credit (Faiella and Natoli, 2018). Furthermore, loans are often collateralized, and there is a significant overlap between the location of debtor companies and the real estate collateral offered as a guarantee. Therefore, loan exposure is highly correlated with collateral exposure, potentially increasing the PD and the loss given default (LGD) if climate risk materializes (Meucci and Rinaldi, 2022).

Hence, integrating climate related factors into credit risk assessment is one of the main issues at the frontier for credit risk management, both at the corporate level (Brogi *et al.*, 2022) and within central banking institutions (Angelini, 2022). However, several complexities arise in this context (Redondo and Aracil, 2024): i) data gaps: usually, only the firm's headquarters is known, with insufficient information on the location of other facilities, such as production plants; ii) natural hazard maps are often not accurate; iii) when reliable hazard maps are available, the empirical evidence on how natural hazards impact businesses remains insufficient, making it challenging to develop reliable estimates of potential damages.

This paper evaluates the effect of physical HG risk on the one-year default probability of a sample of Italian non-financial firms, trying to overcome the above mentioned data issues. First, we derive the exact geographic location of each firm's primary and local units using data from the Italian Business Registry (Infocamere). Second, we assign specific flood and landslide exposure levels to each firm matching geographic local unit location with the 'ISPRA mosaic risk maps' (Loberto and Spuri, 2023). In doing so, we define three discrete risk indicators: one for flood, one for landslides and one for the overall HG risk for each firm, accounting, alternatively, for all local units and for the headquarters only.

We find that roughly 38 per cent of Italian non-financial firms are exposed to HG events, particularly floods. Accounting for local units is important: when considering the headquarters location only, the risk estimation is misrepresented for almost 10 per cent of firms, and 23 per cent if we exclude firms with only one local unit that coincides with the headquarters.

HG risk is especially concentrated in certain regions. Firms in Emilia-Romagna and Tuscany regions are significantly exposed to HG risks in absolute numbers regarding local units and employees. In Emilia-Romagna, almost 55 per cent of local units and 60 per cent of employees are exposed to flood risk. Liguria and Calabria have the highest share of local units exposed to the most severe risk category (7.7 per cent). For landslide risk, Tuscany, Lombardy, and Campania have the highest absolute numbers of exposed employees, whereas Aosta Valley has the most significant relative share, with nearly 40 per cent of employees exposed to landslide risk.

As a third and final step, to assess the effect of natural hazards on firms' creditworthiness, we compute a risk-adjusted financial statement by quantifying the expected damage based on property type (e.g. warehouse, shed, store, etc.) weighted by the risk level. To translate the risk-adjusted financial statement

into a one-year PD, we rely on the Banca d'Italia In-House Credit Assessment System statistical model (or S-ICAS, see Narizzano, *et al.*, 2024). S-ICAS is one of the sources in the Eurosystem Credit Assessment Framework (ECAAF) for assessing the credit quality of eligible assets as collateral in monetary policy operations. Given that S-ICAS rates Italian non-financial firms, whose credit claims serves as collateral, the impact of physical risk on firms' credit profile has implications for collateral availability.

Our estimates indicate that 38 per cent of firms experience a mild deterioration in PDs. The overall impact – in terms of the Eurosystem's Credit Quality Step (CQS) scale – is limited, as only 0.43 per cent of firms transitions to a worse rating class.² However, firms located in high-risk areas experience a significant decline in creditworthiness. The most affected sectors are “Agriculture”, “Transportation and Storage” and “Accommodation and Food Services”. On average, firms in Liguria show the worst deterioration of PD, followed by Aosta Valley and Calabria.

Insurance coverage stands out as a key risk mitigation factor. An analysis based on data from a survey carried out by Banca d'Italia in 2024³ indicate that, for a subsample of firms, insurance against natural hazard can reduce the average PD deterioration by nearly the 50 per cent. This finding is particularly noteworthy given that banks usually do not differentiate between firms insured or uninsured (Gallo *et al.*, 2024). Also, insurance against climate risk contributes to the overall financial stability system (De Polis, 2025).

All in all, despite the high concentration of HG risks in certain regions, and the fact that firms most exposed to HG risks exhibit a notable increase in average PD, our findings indicate that the overall impact on firms' creditworthiness is, on average, not economically significant and may be significantly reduced with an insurance coverage. As a result, the average effect on collateral is also negligible, and at this stage, does not pose a significant constraint on the refinancing capacity of Italian banks.

Our analysis relies on ISPRA hazard maps, whose probabilities are derived from historical observations until 2021. However, climate change is driving a substantial increase in the frequency of extreme natural events globally (World Meteorological Organization, 2025), with particularly pronounced effects observed in Italy. In 2023 floods and river overflows increased by 170 percent with respect to 2022, landslides triggered by heavy rainfall by 64 percent, and flooding events by 12.4 percent (Legambiente, 2023). Therefore, our results should be interpreted as reflecting an average⁴ historical scenario, while recognizing that, in the absence of targeted policy interventions, the frequency and severity of extreme events are expected to rise further (Emambakhsh *et al.*, 2023). When we increase the frequency of HG

² Each CQS corresponds to a broad range of PD values; therefore, minor PD increases may not result in a change of CQS. For further details, see Table 13.

³ Colletti F., Columba F., Cugliari M., Iannamorelli A., Parlamento P., Tozzi L. (2025), Do firms care about climate change risks? Survey evidence from Italy, *Bank of Italy Markets, Infrastructures, Payment Systems Working Paper 70*.

⁴ Average scenario refers to the return period. Return period is an average time statistically measured on extended historic data between floods or landslide to occur.

events using the upper bound available, PD increases double or even triple compared to the baseline with an average PD increase of 32 bp for firms in the highest risk category. The remainder of this paper is organised as follows: Section 2 provides an overview of the state of the art in the assessment of HG risk; Section 3 describes the data sources; Section 4 explains the methodology and Section 5 presents the results. Section 6 provides an analysis about the potential effect on collateral pledged for monetary policy operations and Section 7 concludes.

2. Modelling hydrogeological risk

2.1 Flood

Assessing exposure to natural disasters involves matching flood risk (hazard) data with the share of firms in floodplain areas within each municipality (exposure). Hazard data are typically sourced from the ISPRA mosaic hydrogeological map, providing risk indicators for floods and landslides at the municipal level. For exposure, ISTAT provides the concentration of buildings by municipality. Vulnerability is crucial in assessing the annual potential loss, especially when considering mitigation policies (e.g., insurance or preventive interventions like drainage areas) and flood depth.⁵ A study analyses Dutch banks' exposure to flooding risk, considering mitigation policies and water depth (Caloia, 2021). The author uses private and commercial real estate data, including property quality, the number of floors, and flood depth associated with return periods. Risk mitigation measures, such as insurance covering recovery costs, are also considered.

In Italy, such detailed analysis presents significant challenges, particularly with respect to the availability and accuracy of flood depth data. While the ISPRA hazard maps are the official national reference, they do not provide flood depth information. Alternatively, flood depth maps published by the Joint Research Center (JRC) of the European Commission are available, but they lack the precision required for firm-level analysis (Loberto and Spuri, 2023). A key difference between the two sources lies in the way spatial information is represented. JRC maps are based on raster data, grids of cells where each cell represents a given value. The spatial resolution and accuracy of raster data depend on the size of these grid cells; larger cells lead to less precise boundary definitions. Conversely, ISPRA maps rely on vector data, where features are defined by coordinates in several geometric elements, offering greater accuracy in mapping boundaries and locations. Notably, the JRC itself acknowledges that their maps cannot be considered official flood hazard maps.

Several efforts have been made to estimate flood depth and associated damage. A basic approach involves constructing an index based on historical flood raster data as a proxy for flood depth (Dottori *et al.*, 2018). This index also accounts for flood risk mitigation measures, such as flood management strategies and

⁵ Flood depth refers to the vertical distance between the ground level and the surface of the floodwater during a flood event.

building elevation. Although useful for assessing exposure in complex scenarios, this methodology remains indicative and untested. JRC has also published a mainstream study estimating the so-called Flood Damage Function (Huizinga *et al.*, 2017). This study derives a damage function for each country with available historical data, quantifying the relationship between hydraulic parameters and asset-specific damage in real terms. However, the economic estimation of direct damages remains subject to significant uncertainty, driven by simplifying assumptions and data constraints. In countries without established damage models, transferring damage functions from other regions is necessary, but this can lead to large discrepancies, as such functions often vary substantially. These uncertainties in quantitative damage modelling strongly affect the reliability of detailed economic assessments (Scorzini and Leopardi, 2017). Moreover, model validation is essential when extending hydrogeological risk models to other countries (Molinari *et al.*, 2019). Replicability is only feasible when geomorphological characteristics and precipitation patterns are comparable; otherwise, damages are likely to be underestimated or overestimated (Molinari *et al.*, 2020).

In this context, the River Po District implements a model for hydrogeological risk assessment (Distretto del Fiume Po, 2021) explicitly trained on Italian data to meet the requirements of the Flood Directive. MOVIDA assesses risk for the populations, economic activities, infrastructure, plants, and cultural heritage by considering hazards, exposure, vulnerability, flood depth, damage functions by building type, and recovery costs.

2.2 Landslides

Assessing landslide vulnerability is complex and should consider multiple dimensions, including physical and socioeconomic factors. The physical vulnerability of buildings and infrastructure depends on the intensity of the landslide event and the resistance level of the exposed elements. Studies on landslide risk assessment primarily focus on technical aspects (see UNISDR, 2009; Arrogante-Funes *et al.*, 2021; Roccati *et al.*, 2021; and Novellino *et al.*, 2024 among others). Due to the geological and morphological characteristics of the Italian territory, which is 75 per cent mountainous-hilly, landslides are ubiquitous. Thus, comprehensive inventory projects are essential for landslide risk assessment. The Inventory of Landslide Phenomena in Italy (IFFI Project), carried out by ISPRA and the Regions and Autonomous Provinces, classifies landslides that have occurred nationwide using standardized and shared methods (APAT, 2007). The IFFI Inventory is Italy's most comprehensive and detailed landslide database (Trigila *et al.*, 2010), though it presents some limitations stemming from the heterogeneity of regional sources, subjectivity in mapping procedures, and lack of temporal and typological consistency (Loche *et al.*, 2022).⁶ Despite the availability of alternative sources (e.g., IRPI-CNR inventories or local studies), both

⁶ These differences generate significant spatial biases: in some areas (e.g., Sicily and Calabria), landslide hazard is systematically underestimated, while in other regions such as Piedmont or Lombardy, data coverage is more complete

the scientific community and public authorities consistently rely on ISPRA maps. These maps are the official tool adopted at both national and European levels for hydrogeological risk reporting and management (EU Floods Directive 2007/60/EC), as they ensure methodological harmonization, regional comparability, and institutional legitimacy, while still reflecting the inherent limitations of the underlying models and inventories.

Landslide hazard reflects the probability of a potentially destructive phenomenon of a certain intensity occurring in a given period and area (Varnes, 1984). The primary challenge in landslide hazard analysis is obtaining information on landslide activation dates, which then enables the study of recurrence times. Susceptibility or spatial hazard analysis is typically conducted to identify areas with the highest likelihood of landslide occurrence (Trigila *et al.*, 2013). Unlike flood risk assessment, which often relies on quantitative approaches, landslide risk assessment primarily follows a qualitative methodology. This approach integrates the probability of occurrence with the associated risk level and event magnitude (Iadanza *et al.*, 2021).

3. Data

We rely on three data sources: i) ISPRA georeferenced maps to identify floodable areas and areas exposed to landslide, ii) the Infocamere database with information about the location of primary and secondary units, iii) S-ICAS firms' financial variables.

3.1 Hazard - ISPRA

Given the complex nature of the Italian terrain, with 42 per cent hilly, 35 per cent mountainous, and only 23 per cent flat,⁷ detailed local investigations have led to the zonation of landslide and flood hazards. This work was initially formalised through the 'Piani di Assetto Idrogeologico' (PAI),⁸ which later evolved into 'Piani di Gestione Rischio Alluvioni' (PGRA).⁹ Each of the seven Italian District Basin Authorities (ABD) manages and updates its own PGRA every six years. The current PGRA, covering the period 2021-2027, defines flood scenarios and provides guidance for the design of defensive structures and mitigation strategies. ISPRA periodically updates the hydrogeological hazard maps collecting detailed data about floods and landslides from the ABDs.

Based on the ISPRA maps, a recent study offers a new methodology for assessing flood risk in Italy for residential property (Loberto and Spuri, 2023). Flood risk is assessed through a two-step process: (i)

(Reichenbach *et al.*, 2018). Moreover, the preferential nature of surveys (e.g., along infrastructure or in areas of particular interest) and the uneven use of detection techniques further reduce the reliability of the data at the national scale. Indeed, ISPRA is committed to continuously updating its mosaic.

⁷ Data available at <https://www.istat.it/it/archivio/137001>

⁸ Legislative decree 23 February 2010, no. 49. Transposition of the Floods Directive 2007/60/EC Concerning Flood Risks Assessment and Management

⁹ 2019. ProteggItalia. National Plan for Landslide and Flood Risk Mitigation, Restoration and Protection of the Environment. For a detailed evolution of policies, see Vitale and Meijerink, 2023.

identification of potentially floodable areas based on past events and a forward-looking evaluation, partly accounting for climate change effects; (ii) attribution of a risk level to each area. The risk level differs for flood and land. Flood risk levels convey information about flood return times, while landslide risk levels also provide information about the magnitude of the phenomenon (see Table 1).

Table 1 – ISPRA risk category for flood and landslide¹⁰

Flood	Landslide
HPH – High Probability Hazard (flood return time between 20 and 50 years)	P4 – high (1-30 years) and medium (30-100 years) frequency, high damage magnitude
MPH – Medium Probability Hazard (flood return time between 100 and 200 years)	P3 - high (1-30 years) and medium (30-100 years) frequency, medium damage magnitude OR low frequency (100-300 years), high damage magnitude
LPH – Low Probability Hazard (flood return time longer than 200 years)	P2 – high (1-30 years) frequency, low damage magnitude OR low frequency (100-300 years), medium damage magnitude
	P1 – medium (30-100 years) and low (100-300 years) frequency, medium and low damage magnitude

Unlike the flood hazard mosaic, where an area may be subject to flooding under one or more of three different probability scenarios, the landslide hazard mosaic assigns each portion of the territory to a single hazard class. Therefore, the total area of landslide hazard zones in Italy is equal to the sum of the areas of the four hazard classes.

It is important to notice that ISPRA mosaic risk maps are subject to the typical uncertainties of hydrogeological modelling, such as parameter selection, boundary conditions, calibration, and conceptual structure. However, ISPRA mosaic is embedded within the regulatory framework of the EU Floods Directive (2007/60/EC) and serves as the official tool for hydraulic risk management and assessment at both national and European levels. When ISPRA collects data from the various ADB, it applies harmonization and quality control procedures to ensure consistency and compliance with EU guidelines, and the European Commission itself validates the data. While the maps do not report confidence intervals or uncertainty zones, they are expected to reflect the highest possible level of reliability. Technical literature also highlights that uncertainty is particularly associated with flood depth and flow velocity; variables not yet considered in this work.

¹⁰ ISPRA’s hazard classifications are based on the most recent PGRA, covering the period 2021–2027. Although the PGRA adopts a forward-looking framework, the definition of return periods is still grounded in historical observations. As a result, these return periods may underestimate the true frequency of such events, particularly in light of the recent surge in extreme weather occurrences. Between 2022 and 2023 alone, floods and river overflows increased by 170 percent, landslides by 64 percent, and flooding events by 12.4 percent (Legambiente, 2024).

3.2 Exposure - Infocamere and Cebi/Cerved

When assessing HG risk, it is essential to account for exposure, namely the value of activities susceptible to such events. To this end, we use data from Infocamere to determine the location of primary and local units for each firm assessed by the S-ICAS model (Section 3.3). Infocamere provides information on the establishment, modification, and cessation of all enterprises, regardless of their legal form or economic sector of activity, with headquarters or local units (e.g., offices, plants, warehouses) within the national territory, as well as other entities mandated by law. Hence, we retrieve detailed information on company headquarters (*Sede Legale*) and local units (*Unità Locali*) across Italy, including their functional type. Given that Infocamere classifies local units into over 100 types, we consolidate these into four primary categories based on their roles in the production cycle: warehouses (supply and storage), plants (production), shops (sales), and offices (administrative functions). Warehouses and Shops have the highest shares (around 29 per cent in both cases) of the industrial building distribution, followed by Offices (Table 2). The overall distribution aligns with the core activities and patterns of the NACE sectors. Trade accounts for 26.28 per cent of the total buildings, followed by Manufacturing (19.44 per cent) and Construction (10.97 per cent). Additionally, Trade holds the largest shares of shops (9.17 per cent) and warehouses (14.07 per cent), whereas Manufacturing features the highest proportion of plants (13.60 per cent), reflecting the primary business activities of these sectors.

To evaluate the significance of each local unit, we follow a hierarchical approach that prioritizes employment information while ensuring that all premises are considered in the assessment of exposure. We use employee distribution data at the municipal level for each firm. In cases where a single building exists within a municipality, we get the exact number of employees for each location. For municipalities with multiple buildings, we assume a uniform distribution: the proportion of employees relative to the total number of buildings in the municipality determines the relative importance of each unit.¹¹ The employment information is then complemented with an alternative allocation based on the number of premises. By construction, this step assigns a residual weight also to premises without employees, which would otherwise be disregarded in the assessment of risk exposure. The final distribution combines the two dimensions, with a higher weight given to employment (75 per cent) and a smaller but non-negligible weight to premises (25 per cent).

¹¹ This is the best proxy available to provide a municipal-level approximation of the number of employees, and it has also been used in other studies (Trigila *et al.*, 2021; Meucci and Rinaldi, 2022; Loberto and Spuri, 2023; Loberto and Russo, 2024a).

Table 2 – Distribution of industrial building by category and NACE sector¹²*(percentage values)*

NACE SECTOR	OFFICE	PLANT	SHOP	WAREHOUSE	OTHER	TOTAL
Agriculture	0.1	1.3	0.1	0.2	0.0	1.8
Mining	0.0	0.1	0.0	0.1	0.0	0.3
Manufacturing	1.9	13.6	1.5	2.2	0.1	19.4
Electricity	0.4	1.0	0.1	0.0	0.0	1.5
Waste management	0.3	0.7	0.1	0.2	0.0	1.3
Construction	1.6	0.3	0.5	8.5	0.1	11.0
Trade	2.0	0.7	9.2	14.1	0.3	26.3
Hosting services	2.8	0.2	0.3	3.3	0.1	6.8
Transporting	0.3	0.1	7.0	0.2	0.2	7.8
ICT	2.8	0.0	0.2	0.1	0.0	3.1
Real Estate	0.3	0.0	0.0	0.0	0.1	0.4
Professional services	0.6	0.1	6.1	0.1	0.0	6.8
Administrative services	4.3	0.1	0.2	0.1	0.1	4.9
Education	2.7	0.1	0.5	0.3	0.0	3.7
Health services	0.5	0.1	0.1	0.0	0.4	1.0
Entertainment	0.8	0.1	2.0	0.0	0.0	3.1
Other services	0.1	0.0	1.1	0.0	0.0	1.3
TOTAL	21.9	18.6	28.9	29.5	1.6	100.0

Our dataset includes 745,370 local units, corresponding to 366,799 active firms as of December 31, 2023, employing a total of 7.2 million workers. We integrate Infocamere data with firms' financial statement data for 2022, sourced from the *Sistema Informativo Economico-Finanziario* (SIEF) of Banca d'Italia. SIEF incorporates data from Cebi (*Centrale dei Bilanci*) and Cerved databases. While the Cebi database primarily covers medium and large Italian firms and a limited number of small firms, Cerved provides a broader scope, encompassing nearly all small and micro limited-liability firms (Giovannelli *et al.*, 2020).

The average number of employees varies significantly across NACE sectors (Table 3 – Panel A). The mean number of employees by firm is 26, with peaks in sector in Hosting services at 60, and Administrative services at 67. However, the median number of employees is much lower at 6, reflecting the dominance of micro firms, which constitute 67 per cent of the sample. Firms have, on average, two buildings, while the median remains one, again influenced by micro-firm prevalence. The average asset value is €8 million while revenues average €7 million. For both total assets and revenues, Electricity records the highest average, respectively at €41 million and €53 million.

When analysing firm characteristics by size,¹³ the averages become closer to the median values (Table 3 – Panel B). Micro firms average 5 employees, small firms 18, medium firms 69, and large firms 565,

¹² See Appendix A for full NACE Rev. 2 sector definitions. From now on, we refer to NACE sector with letters.

¹³ According to the European Commission definition (Recommendation 2003/361/EC)

although the latter exhibit significant variability, with a standard deviation approximately equal to 6,000. Large firms average 14 local units, compared to just one for micro firms. The average asset value ranges from €228 million for large firms to €1 million for micro firms. Average revenues vary similarly, from €1 million for micro firms to much higher values for larger firms. The final dataset is obtained by merging the firm information in the S-ICAS database with information about the geographic location of primary and local units, the number of employees for each firm's unit, and the risk level based on ISPRA maps.

Table 3 - Summary Statistics

	Number of firms	Employees (#)			Business Units (#)			Assets (€ mln)			Revenues (€ mln)		
	366,799	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Panel A: Nace Sector													
Agriculture	7,241	15	47	6	2	1	1	5,101	18,817	1,439	2,879	20,916	453
Mining	827	12	17	8	2	2	2	7,176	18,924	2,787	3,656	12,665	1,472
Manufacturing	76,103	29	175	11	2	3	1	10,229	102,909	1,945	10,120	115,132	1,923
Electricity	3,881	34	434	4	3	12	2	40,603	712,313	2,044	52,687	1,115,254	308
Waste management	3,351	45	184	12	3	6	2	14,331	75,573	2,605	9,493	28,916	2,592
Construction	52,606	12	37	6	1	1	1	3,725	26,434	1,146	2,667	11,532	983
Trade	78,859	16	147	5	2	9	1	5,168	87,474	1,073	8,901	168,486	1,385
Hosting services	16,322	60	3,426	9	3	103	1	14,097	915,618	1,056	6,394	87,619	1,289
Transporting	27,349	17	101	7	2	5	1	2,573	15,376	500	1,316	7,956	497
ICT	11,453	26	157	6	2	3	1	8,882	212,225	690	4,281	58,295	528
Real Estate	40,137	11	92	1	1	1	1	4,738	22,326	1,316	502	2,660	142
Professional services	16,685	15	105	4	2	4	1	2,655	16,073	655	2,242	17,437	520
Administrative services	11,815	67	791	7	2	6	1	4,754	71,232	675	4,294	41,024	685
Education	2,132	15	34	6	2	3	1	1,447	4,689	466	1,167	3,881	419
Health services	9,080	47	181	9	3	5	1	3,734	19,787	701	3,066	14,076	759
Entertainment	5,158	15	83	3	2	2	1	2,808	24,525	505	1,681	13,117	351
Other services	3,800	14	52	5	2	2	1	1,432	5,111	370	1,104	2,887	385
Panel B: Firm Size													
Large	5,191	569	6,323	217	15	187	4	226,635	1,833,720	73,887	219,727	1,222,443	78,007
Medium	27,677	70	119	53	3	5	2	19,513	26,824	14,852	18,306	17,440	14,294
Small	117,283	18	34	13	2	2	1	4,044	6,514	2,917	3,492	3,702	2,612
Micro	216,638	5	19	4	1	1	1	874	2,225	559	646	727	450

3.3 The S – ICAS model

Since 2013, Banca d'Italia has been managing the ICAS model to assess the creditworthiness of a sample of Italian non-financial firms,¹⁴ whose loans may qualify as eligible collateral for monetary policy operations under the ECAF. The ICAS rating process follows a two-stage approach, combining a statistical model, the S-ICAS, with an expert assessment to determine the firm's final rating. The statistical

¹⁴ Non-financial firms in the S-ICAS sample: i) are incorporated as a limited liability company in Italy; ii) publish a financial statement; and iii) have an exposure towards the banking system, as reported in the National Credit Register (NCR).

model is the first stage of the rating process, and it produces estimates of the PD over a one-year horizon for about 370,000 non-financial firms every month.¹⁵

4. Methodology

4.1 Geo-referencing local units

A prerequisite for quantifying physical risk is the geographical location of the firm's primary and secondary local units. This process, known as geocoding, entails converting textual addresses into latitude and longitude coordinates. To ensure accurate geolocation of local units, a geocoding server is essential, as it facilitates the reliable mapping of entities to their physical locations. Given the critical nature of this task, we opted for the ESRI – a worldwide leader Geographic Information Systems (GIS)¹⁶ – paid APIs,¹⁷ which stand out for their exceptional accuracy and reliability in geospatial data processing.

Geocoding in the ESRI system consists in a multi-step process that converts addresses into geographic coordinates with high accuracy. First, addresses are cleaned and standardized to ensure consistency in formatting—this means fixing abbreviations, punctuation, and other inconsistencies. Then, each part of the address (like street name, house number, and postal code) is checked against official reference data.

Once the address is properly formatted, it is sent to the ESRI API, which generates possible location matches and ranks them based on similarity. Each match receives a confidence score, and only those above 90 per cent are automatically accepted. If an address doesn't meet this threshold, it is flagged for manual review.

To further improve accuracy, ESRI's results are compared with other geocoding services like Nominatim¹⁸ (OpenStreetMap) and Google Maps.¹⁹ This helps validate the 90 per cent confidence threshold and ensures the best balance between accuracy and reliability.²⁰

Using data from Infocamere, we identify 366,799 primary offices and 378,571 local units for the firms evaluated by the Stat – ICAS model as of December 31, 2023. We validate the locations on a sample basis

¹⁵ See Narizzano *et al.*, 2024 for further details.

¹⁶ GIS refers to a technological framework designed for collecting, managing, analysing, and visualizing geospatial data, enabling the exploration of spatial patterns, relationships, and trends across various disciplines, including urban planning, environmental science, and risk assessment.

¹⁷ API (Application Programming Interface) is a structured set of protocols, routines, and tools that enables different software systems or components to communicate and exchange data, often facilitating the integration of third-party functionalities into applications. The ESRI paid APIs integrate customizable advanced algorithms for address parsing, candidate location identification (both in rural and urban areas), and scoring mechanisms that ensure robust geocoding results.

¹⁸ Nominatim is a geocoding tool provided by OpenStreetMap that transforms textual addresses into geographic coordinates and vice versa, utilizing open-source geospatial data curated and maintained by a global community.

¹⁹ Google Maps is a comprehensive geospatial platform developed by Google, offering services such as geocoding, mapping, and navigation through APIs, supported by an extensive and regularly updated global dataset.

²⁰ For further details about the geocoding algorithm see Appendix C.

through web access to Telemaco²¹ and verification of business registry records. We also exclude foreign local units. In total, there are 745,370 positions to be geocoded. This comprehensive dataset forms the foundation for our geocoding analysis, ensuring that all relevant local units are accurately accounted for in the subsequent risk assessment.

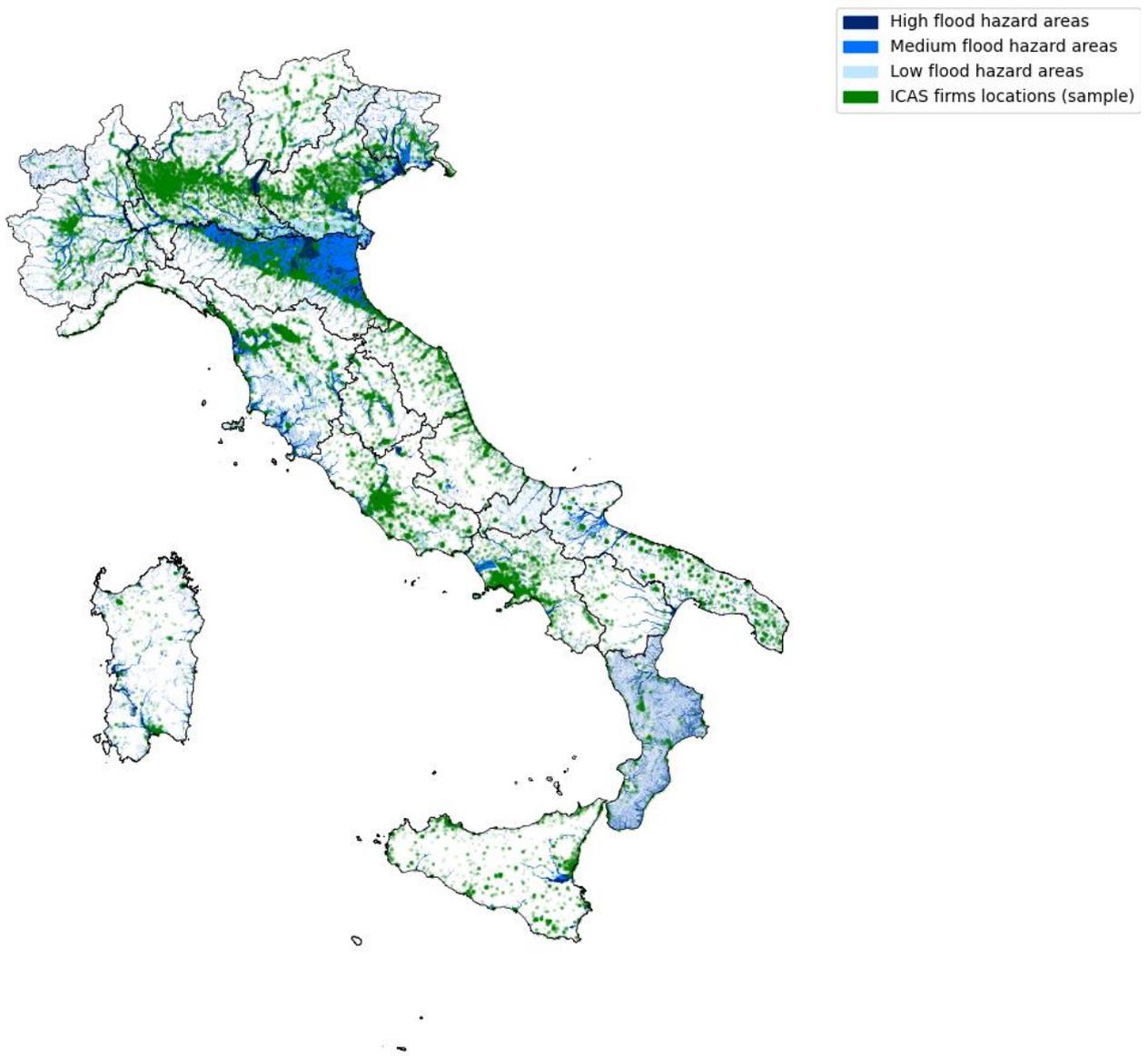
The resulting dataset enriches the geocoded data with risk attributes for both flood and landslide hazards. Each local unit is assigned a risk level, and for those falling within multiple hazard zones, attributes for each distinct risk are stored. The outcome provides a granular risk profile that captures the multi-dimensional nature of hydrogeological threats (Figure 1).

The validation is performed by manually cross-checking a subset of local unit coordinates against the ISPRA hazard maps using an external GIS tool (Loberto and Russo, 2024b). Specifically, we selected a sample of locations, overlaid them on the official ISPRA polygons, and verified that the spatial join correctly assigned each unit to the expected hazard category. This consistency check confirmed the reliability of the integration procedure. The results illustrate the spatial alignment between the mapped local units and the ISPRA-defined flood and landslide hazard zones (Figure 1 and 2). The left panel highlights flood risk zones, with darker shades indicating higher risk levels, while the right panel shows landslide risks using a gradient of red to represent severity. The green dots marking local unit locations show their spatial correspondence with the hazard zones.

This enriched geospatial dataset forms the backbone for subsequent risk analysis, enabling the calculation of firm-level risk indicators that aggregate hazard exposure across all local units. These indicators are weighted by the operational importance of each unit, providing a comprehensive measure of hydrogeological exposure for integration into financial and credit risk models.

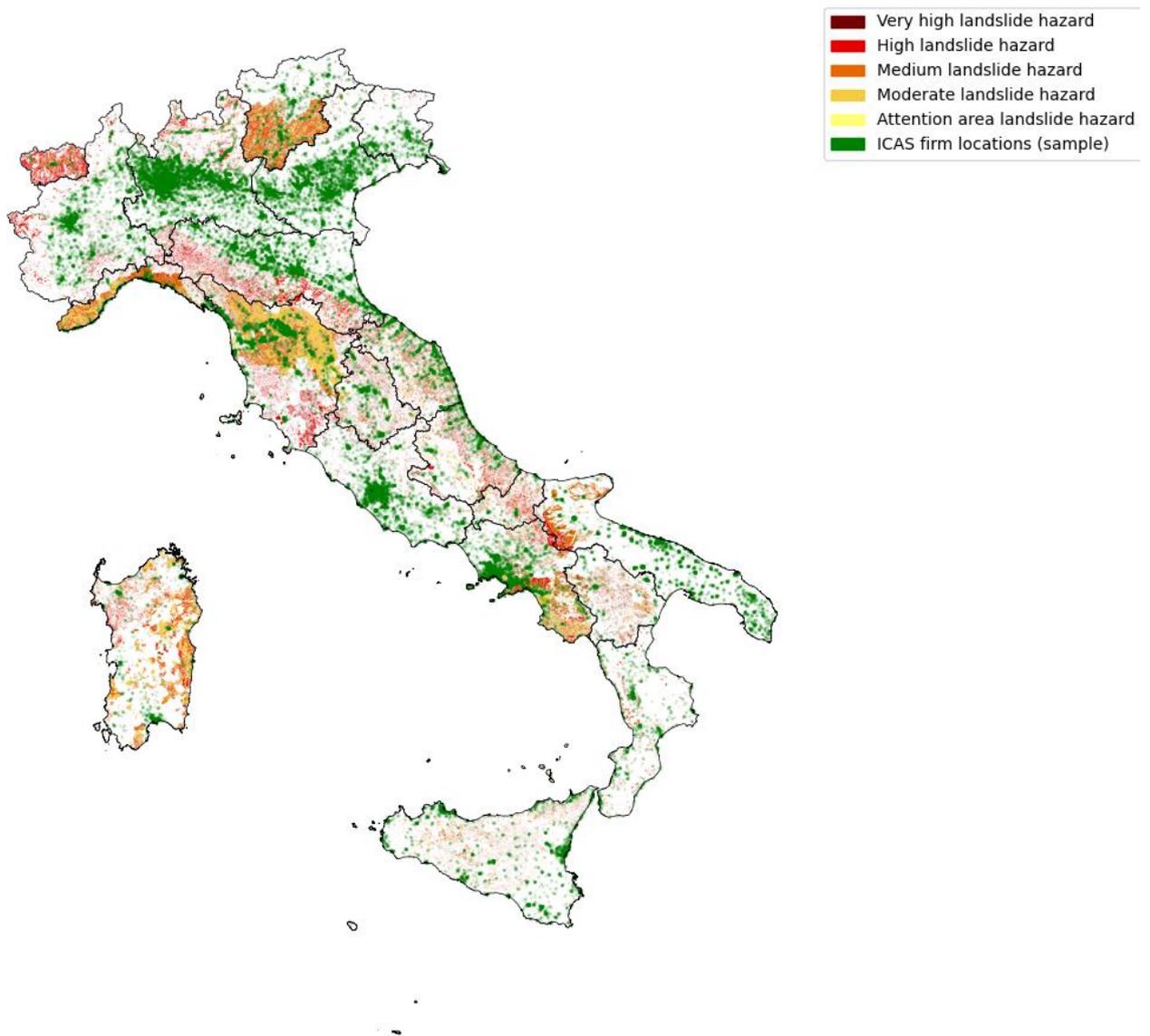
²¹ Telemaco is the online access method to the Italian Business Registry database, and it allows the consultation of ordinary and historical business records, company financial statements, and documents of all enterprises, providing the primary legal, economic, and administrative information.

Figure 1 - ISPRA flood mosaic risk maps and S-ICAS firms distribution



Note: ISPRA mosaic risk maps for flood and a sample of about 60.000 S-ICAS firms' distribution (green dots). See Appendix C for Italy political map at regional level.

Figure 2 - ISPRA landslide mosaic risk maps and S-ICAS firms distribution



Note: ISPRA mosaic risk maps for landslide and a sample of about 60.000 of S-ICAS firms' distribution (green dots). See Appendix C for Italy political map at regional level.

As described in Section 2, each risk category for flood and landslide is associated with a range of return time. In order to compute risk-adjusted financial statement, we need to turn the return period into the annual probability of occurrence of the HG event.

To do so, we rely on the hydraulic engineering formula in Equation 1. Given that T is the average return time, the annualised probability of occurrence is:

$$p = 1 - \left(1 - \frac{1}{T}\right)^N \quad \text{with} \quad N = 1 \quad (1)$$

In our case, we set $N=1$ since we are interested in the probability of the event occurring within the current year. However, when the event is associated with a time interval $[T_1, T_2]$, selecting a single representative

value requires a methodologically sound approximation. In this paper, we choose to use the probability corresponding to the average return period, calculated as the arithmetic mean of the two return periods defining the interval (Table 4).²² Studies in the field of extreme value processes, such as Raschke (2021), show that the mean of two return periods can be used to derive a so-called *combined return period*, defined as $T_c = \frac{T_1+T_2}{2}$, whose exceedance frequency is therefore $1/T_c$.

Table 4 – Annualised probability of occurrence of the HG events

Flood	Landslide
HPH: T = [20; 50] → $\bar{T} = 35 \rightarrow p = 0.028$	P4: T = [1; 30] → $\bar{T} = 15 \rightarrow p = 0.067$
MPH: T = [100; 200] → $\bar{T} = 150 \rightarrow p = 0.007$	P3: T = [30; 100] → $\bar{T} = 65 \rightarrow p = 0.015$
LPH: T > 200 → $\bar{T} = 200 \rightarrow p = 0.005$	P2: T = [100; 300] → $\bar{T} = 200 \rightarrow p = 0.005$
	P1: T > 300 → $\bar{T} = 300 \rightarrow p = 0.003$

Note. The table reports for flood and landslides the risk category, the range of return time, the average time and the average annualised probability of occurrence. For landslide, we consider the more frequent range of return time for each risk category. For the lowest risk category, we have adopted a prudential approach by applying the highest available frequency (own calculation on ISPRA data).

As pointed out in Section 2, the Infocamere database also provides detailed information about the type of industrial building. We provide the distribution of local units by risk category for flood and landslide (Table 5). For both flood and landslide, most of industrial buildings are located in a non-risk area (69.7 per cent and 92.4 per cent respectively). Nevertheless, 6 per cent and almost 12 per cent of local units are exposed, respectively, to the highest and medium flood risk categories (Table 5 –Panel A).

Table 5 - Distribution of industrial building by risk category

(percentage values)

ISPRA risk category	Office	Plant	Shop	Warehouse	Other	Total
Panel A: Flood						
0	15.7	12.6	20.0	20.4	1.0	69.7
LPH	2.7	2.4	3.8	3.6	0.2	12.7
MPH	2.4	2.4	3.2	3.5	0.2	11.6
HPH	1.2	1.1	1.9	1.8	0.1	6.0
Panel B: Landslide						
0	20.5	17.0	26.5	27.1	1.4	92.4
P1	0.7	0.6	1.0	1.0	0.1	3.3
P2	0.6	0.5	0.8	0.8	0.1	2.8
P3	0.2	0.2	0.3	0.3	0.0	1.0
P4	0.1	0.1	0.2	0.2	0.0	0.6

As a final step, we include information from the Infocamere database about the number of employees for each firm at municipal level. By matching these data with the locations, we can determine the number of

²² The assumptions regarding return time are critical for the estimation of the expected losses due to HG risks. See Appendix D for alternative hazard probability calculations.

employees for each local unit at municipal level. If the location is not available or cannot be matched, we assume a uniform distribution of the firm's total number of employees across its local units. This step is crucial for assigning the relative importance of each local unit to the overall firm operations.

4.2 Risk-adjusted firms' financial statement

Drawing from probability theory, we consider two states of the world: i) the HG event occurs this year with probability p , and ii) the HG event does not occur this year, with probability $1-p$. Based on this framework, we can estimate the financial impact of HG events by assessing potential production disruptions on the income statement and evaluating expected asset losses on the balance sheet.²³

A production halt directly affects the revenue stream, which in turn influences other key financial variables such as costs, value added, EBITDA, EBIT, and net income. To quantify this impact, we follow a two-step stage approach.

First, we determine the contribution of each local unit to total revenues, starting from local unit relative importance (see Section 3.2). In this step, we assign greater weight to local units that play a critical role in production and sales activities, such as warehouses, plants, and retail stores. The weighting procedure involves two steps: i) the weights of the critical assets are rescaled to sum to 100 per cent; ii) the final weight is computed as a convex combination of the rescaled weights (75 per cent) and the original employee-based weights (25 per cent), thereby preserving a residual contribution from non-critical local units.²⁴ This procedure ensures that the revenues expected loss estimation appropriately reflects the operational relevance of each local unit.

Second, we assume that production or revenue generation at the affected site ceases for a duration that varies based on the level of flood or landslide risk. Specifically, operations are disrupted for 6, 4, and 2 months depending on the flood risk category, and for 8, 6, and 4 months in the case of landslides, as reflected in Equation 1. This structured approach enables a systematic assessment of the financial consequences of extreme events on firms. Then the expected loss of revenues for firms i is:

$$ELrevenues_i = revenues_i \sum_k [exposure_{i,k} \times \sum_j (hazard_{k,j} \times disruption_{k,j})] \quad (1)$$

Where $revenues_i$ is the total revenues for firm i , $exposure_{i,k}$ is the relative importance of site k for firm i , $hazard_{k,j}$ is the probability of occurrence of the j -th HG event (flood or landslide) in site k and $disruption_{k,j}$ is the number of months in a year (in percentage) in which the production is disrupted in

²³ Financial statement data refer to 2022.

²⁴ For example, consider a firm owning three premises: a retail store (40 per cent), a production facility (30 per cent), and an office (30 per cent). The store and facility are identified as critical. Their rescaled weights become approximately 57.14 per cent and 42.86 per cent, respectively. The final weights are then calculated as follows: store 52.86 per cent, facility 39.64 per cent, office 7.5 per cent.

site k for the occurrence of the j -th HG event. Then, the HG risk-adjusted value of revenues for firm i is defined as follows:

$$Revenues_i^{HG} = Revenues_i^{2022} - ELrevenues_i^{2022} \quad (2)$$

Where $Revenues_i^{2022}$ are the revenues of firm i realized in fiscal year 2022.

From a different point of view, going back to probability theory, the HG risk-adjusted revenues could be computed as the sum of the variable in the two states of the world for each local unit k (the j -th HG event happens with probability $hazard_{k,j}$ and the j -th HG event does not occur with probability $1 - hazard_{k,j}$):

$$Revenues_i^{HG} = revenues_i^{2022} \{ \sum_k [(exposure_{i,k} \times \sum_j (1 - hazard_{k,j}))] + \sum_k [exposure_{i,k} \times \sum_j (hazard_{k,j} \times (1 - disruption_{k,j}))] \} \quad (3)$$

Additionally, a production disruption reduces costs. We assume that the reduction of revenues is transmitted to variable and labour costs using elasticities estimates at NACE sector level (see Appendix B for further details on elasticity estimation). A percentage reduction g_R in revenues corresponds to a percentage change in variable costs $g_{VC,R} = \eta_{VC} g_R$ and a percentage change in labour costs $g_{LC,R} = \eta_{LC} g_R$, where η_{VC} and η_{LC} are the elasticity of variable costs to revenues and the elasticity of labour cost to revenues, respectively (De Socio *et al.*, 2020). Therefore, we reduce variable and labour costs accordingly. For the remaining variables in the income statement, we adopt the simplifying assumption of zero elasticity of interest expenditures to revenues. Fixed costs, such as amortization and depreciation, are assumed to remain stable.

We augment impairment losses, reflecting the expected loss in assets due to HG risk. We evaluate the expected losses due to an HG event on the balance sheet asset side and adjust the liabilities side accordingly. An HG event can directly affect Property, plant and equipment (PPE) and Warehouse inventories (WI). To compute the expected loss for PPE, we consider the annualised probability of the HG event associated with the specific local unit (hazard). The contribution to the total value of this balance sheet item is computed as the relative share of employees for the local unit times the total value of PPE (exposure). For WI, we follow the same approach used for revenues and overweight the relative importance of warehouses that are obviously more suited for the storage of raw materials and inventories.

To determine the expected loss, we assume that the assets lose 60 per cent of their value in case of a flood event (Huizinga *et al.*, 2017; Loberto and Spuri, 2023).²⁵ For landslides, given that a magnitude class is associated with each risk category, we apply different assumptions about the asset damage according to

²⁵ Huizinga (2017) estimates damage functions based on parameters including flood depth. In the absence of this data, we adopted the average damage rate for commercial properties in Europe, namely 60 per cent, covering depths from 0 to 6 meters. Also, from a prudential regulatory perspective, under the basic IRB approach, the Loss Given Default (LGD) – analogous to vulnerability – is set by supervisory authorities at 60% for unsecured corporate exposures (Basel II and subsequent frameworks). See Appendix D for simulations with other values, such as 30 per cent and 90 per cent.

different risk areas. Thus, P4 is associated with a loss of 80 per cent of the asset value, P3 of 60 per cent, P2 of 40 per cent and P1 of 20 per cent (vulnerability).

Hence, the expected loss on the l -th asset (PPE or WI), given the contribution of site k for firm i in case of flood, landslide or both is given by:

$$EL_{asset_{i,l}} = \sum_k [exposure_{i,k} \times asset_l \times \sum_j (vulnerability_{k,j} \times hazard_{k,j})] \quad (4)$$

Hence, from the expected loss, we derive the new value of asset l for firm i :

$$IV_{i,l}^{HG} = IV_{i,l}^{2022} - EL_{asset_{i,l}} \quad (5)$$

Where $IV_{i,l}^{HG}$ is the l -th item new value that accounts for HG risk, $IV_{i,l}^{2022}$ is the l -th asset value recorded in the 2022 balance sheet.

The total amount of the expected losses for all the assets of the firm is equal to the impairment losses considered in the risk-adjusted income statement.

Finally, to calculate net income, we apply a tax rate of 28 per cent to pre-tax income, corresponding to the median effective tax rate and aligning with the IRES and IRAP tax rates (De Socio *et al.*, 2020).

After the calculation of the HG risk-adjusted income statement, it is possible to re-compute all the balance sheet variables. For the accounting principle, we get the firm's equity at the end of the year by adding the net profits or losses for the year to the equity recorded at the end of the previous year. Similarly, we also take into account a potential reduction in liquidity due to the HG expected losses. If the resulting expected liquidity shortfall cannot be fully offset by the beginning-of-period liquidity, the residual liquidity requirement is assumed to be met through an increase in short-term financial debt.²⁶

In conclusion, based on the revenues and cost changes and the estimation of the reduced values of balance sheet assets, we compute the HG risk-adjusted income statement and the HG risk-adjusted balance sheet (Table 6 and 7 respectively). A '+' ('-') indicates an increment (reduction) in the HG risk-adjusted value compared to the original financial statement. Variables with '=' are assumed to remain stable.

²⁶ We assume a maximum reduction of liquidity equal to 90 per cent of the initial value. This hypothesis derives from the fact that firm prefer, whenever possible, to keep a minimum amount of liquidity for operating needs (De Socio *et al.*, 2020).

Table 6 – Transmission of the HG risk on Income Statement

Income Statement (Reclassified)	Effect
+ Net revenues	$-\Delta\text{Rev}^1$
- Variable costs	$-\Delta\% \text{Rev} \times \eta_{\text{VC}}^2$
Gross Profit	-
- Labour costs	$-\Delta\% \text{Rev} \times \eta_{\text{LC}}^3$
EBITDA	-
- Depreciation and Amortisation	=
EBIT	-
+ Financial income	=
- Interest expenses	=
- Impairment losses	$-\sum \text{EL}_{\text{Asset}_i}^4$
EBT	-
- Tax expenses	$\Delta\text{EBT} \times (1-t)^5$
Net Income (Loss)	-

Note: Reclassified Income Statement. Items on the LHS column, effects on the items on the RHS column. $-\Delta$ is a pure variation, $-\Delta\%$ is a percentage variation, EL is the expected loss. 1) From Equations 2 and 3, we get that $\Delta\text{Rev} = \text{Revenues}^{2022} - \text{Revenues}^{\text{HG}}$; 2) Percentage change in variable costs depending on the percentage reduction in revenues and on the elasticity of variable costs to revenues; 3) Percentage change in labour costs depending on the percentage reduction in revenues and on the elasticity of labour costs to revenues; 4) total amount of the expected losses for all the assets of the firm (from Equation 4); 5) Tax saving due to the decrease of pre-tax income (EBT).

Table 7 - Transmission of the HG risk on Balance Sheet

Balance Sheet (Assets)	Effect
Fixed Assets	-
Property, plant and equipment	$-\sum \text{ELPPE}_i^1$
Current Assets	-
Cash and equivalents	-
Inventories	$-\sum \text{ELWI}_i^2$
Total Assets	-
Balance Sheet (Liabilities and Equity)	Effect
...	
+ / - Net Income (Loss)	- $\Delta \text{Net Income}^3$
Equity	-
...	
Long-Term Debt	=
...	
Short-Term Debt	+
Short-term financial debt	+
Total Liabilities and Equity	-

*Note: Balance sheet – Asset side and Liabilities side. Items on the LHS column, effects on the items on the RHS column.
1) Sum of the expected loss on local units classified as PPE computed as in Equation 4; 2) Sum of the expected loss on WI computed as in Equation 4; 3) Change in Net Income resulting from the changes in Income Statement.*

The results of the financial statement HG risk-adjusted recalculation under the assumption of two states of the world, are then plugged into the S-ICAS model to determine the HG risk-adjusted PDs of Italian non-financial firms.

5. Results

5.1 Discrete indicators

To evaluate the risk exposure of Italian non-financial firms, we develop three discrete indicators, each ranging from 0 (no risk) to 3 (highest risk). These indicators assess exposure to flood, landslide, and aggregate HG risks. Using risk categories assigned to individual sites by ISPRA, we calculate a firm-level indicator based on the sum of the weighted exposure of each local unit to the corresponding risks. We subsequently reclassify these scores into discrete values between 0 (no risk) and 3 (highest risk). We adopt a conservative approach for the aggregate HG risk indicator, taking the highest risk value (flood or landslide).

Most firms are located in areas with no significant HG risk (Table 8 – Panel A). Flood risk is more widespread than landslide risk, particularly at lower severity levels. Approximately 33 per cent of Italian non-financial firms are exposed to flood risk, while 8 per cent are vulnerable to landslides. These figures are broadly in line with the latest ISPRA report (Trigilia *et al.*, 2021), which estimates that around 40 per cent of local units face flood risk, and 6 per cent are at risk of landslides. Overall, based on the aggregate HG risk indicator, approximately 38 per cent of Italian non-financial firms are exposed to some level of HG risk, compared to 34 per cent of firms when considering the headquarters only (Table 8 – Panel B). These findings highlight the importance for risk assessment of locating local units beyond the headquarters in risk assessment. Ignoring branches, as has been common in previous studies (e.g., Fatica *et al.*, 2024; Clò *et al.*, 2024), can alter the risk exposure estimation. Our analysis shows that focusing solely on headquarters locations has some limitations. Specifically, when exposure is measured at the headquarters level, risk could be overestimated or underestimated depending on the headquarters location compared to other local units. In our sample, discrepancy in risk classification occurs for almost 9 per cent of the firm.²⁷ However, this percentage rises to 23 per cent if we exclude firms with only one local unit that coincides with the headquarters.²⁸

²⁷ Risk estimates based only on headquarters lead to underestimation of HG risk for 6 per cent of firms and overestimation of risk for 3 per cent of firms.

²⁸ Almost 60 per cent of firms in our sample are micro firms that usually have just one local unit.

Table 8 - Physical risk indicators

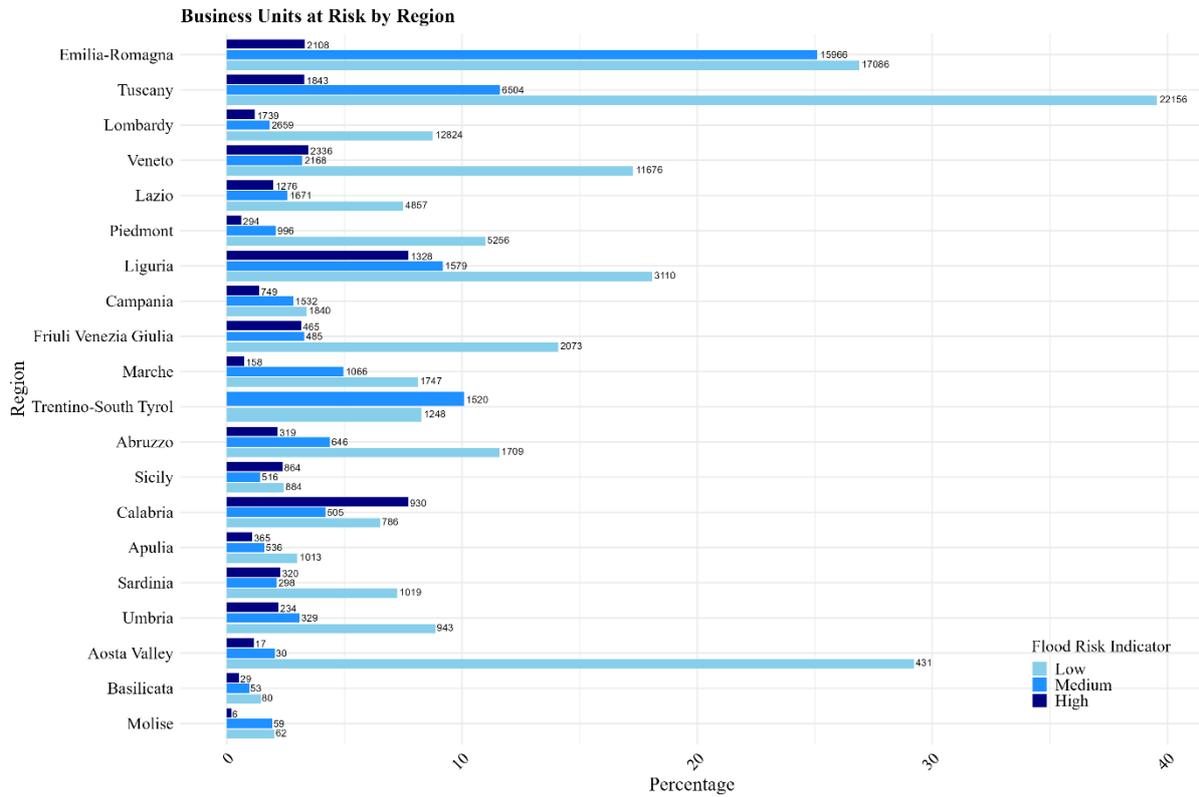
Risk Indicator	Flood (% firms)	Landslide (% firms)	HG (% firms)
Panel A: All local units			
0	66.7	91.8	62.1
Low	15.5	4.3	16.8
Medium	12.7	2.7	14.9
High	5.1	1.2	6.2
Panel B: Only headquarters			
0	70.6	92.8	66.3
Low	12.3	3.2	13.3
Medium	11.4	2.7	13.5
High	5.6	1.4	6.8

Note: Indicators based on own calculations accounting for all local units (Panel A) and for headquarters only (Panel B). The first column refers to flood risk, the second one to landslide risk and the third one to HG risk.

Emilia-Romagna and Tuscany are the most affected regions by flood risk, both in the absolute number of local units and in their share within the region (Figure 3). In Emilia-Romagna, almost 55 per cent of local units are located in risky areas; the percentage is alike for Tuscany (54 per cent); however, in most cases this concerns the least severe risk category. Liguria and Aosta Valley also exhibit a remarkable exposure, with nearly 35 per cent and 32 per cent of local units in risky areas. Liguria and Calabria have the highest share of local units exposed to the most severe risk category (7.7 per cent).

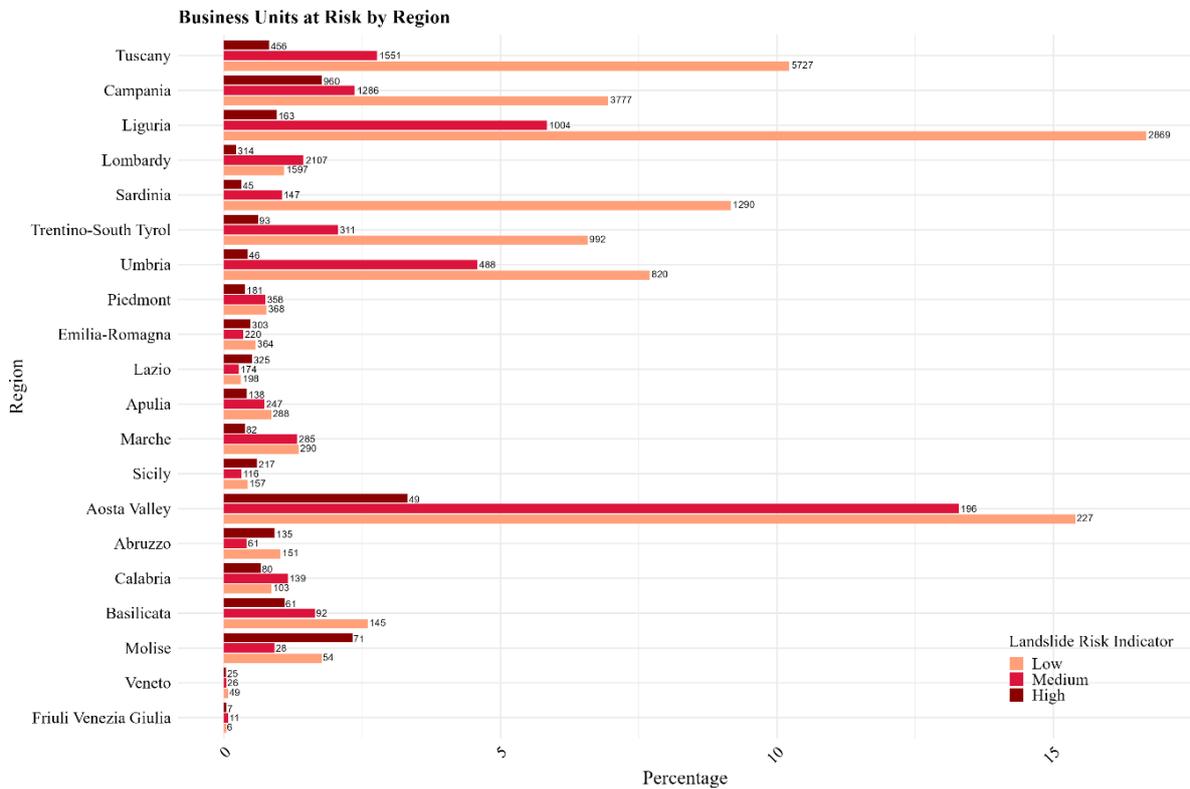
The picture slightly changes when landslide risk is considered (Figure 4). Tuscany, Campania and Liguria are the most affected regions in absolute terms. In Tuscany, nearly 7,000 local units are located in areas categorized at low or medium risk levels (approximately 13 per cent of the total). Campania has nearly 4,000 units in the low risk level. About 17 per cent of branches in Liguria are exposed to the lowest risk category, while 6 per cent face medium risk. Aosta Valley exhibits the highest overall share of local units exposed to risk (32 per cent) and the highest proportion of premises in the most severe risk category (3.3 per cent).

Figure 3 – Share and number of local units exposed to flood risk by region



Note: absolute numbers are shown near the bars, while shares are along the horizontal axis.

Figure 4 - Share and number of local units exposed to landslides risk by region

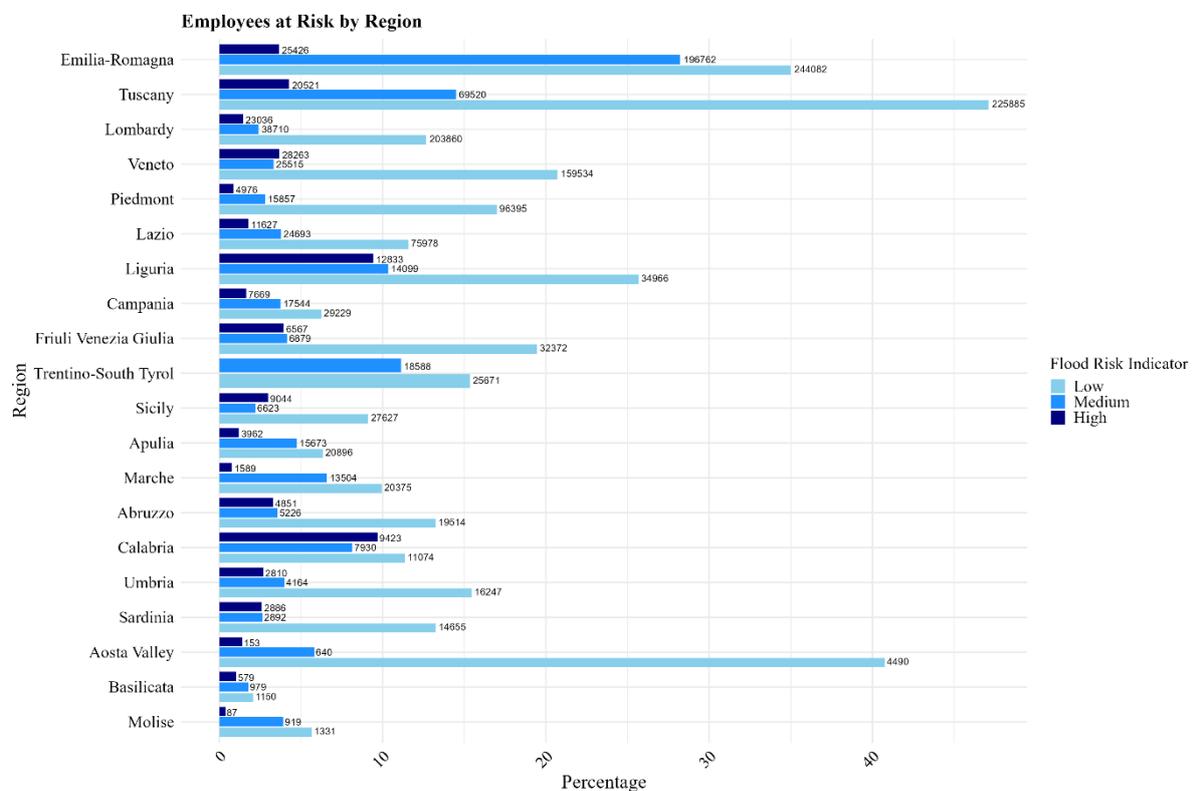


Note: absolute numbers are shown near the bars, while shares are along the horizontal axis.

The exposure of employees broadly mirrors the distribution of local units (Figure 5). Emilia-Romagna, Tuscany, Veneto, and Lombardy are the most affected regions in terms of absolute number of employees. In Emilia-Romagna, 466,260 employees are exposed to flood risk, Tuscany accounts for three quarters as many exposed employees as Emilia-Romagna, and Veneto for a half. In percentage terms, Emilia Romagna and Tuscany have the highest share of exposed employees (roughly 65 per cent). Liguria and Calabria have the highest relative exposure (almost 10 per cent) in the most severe category.

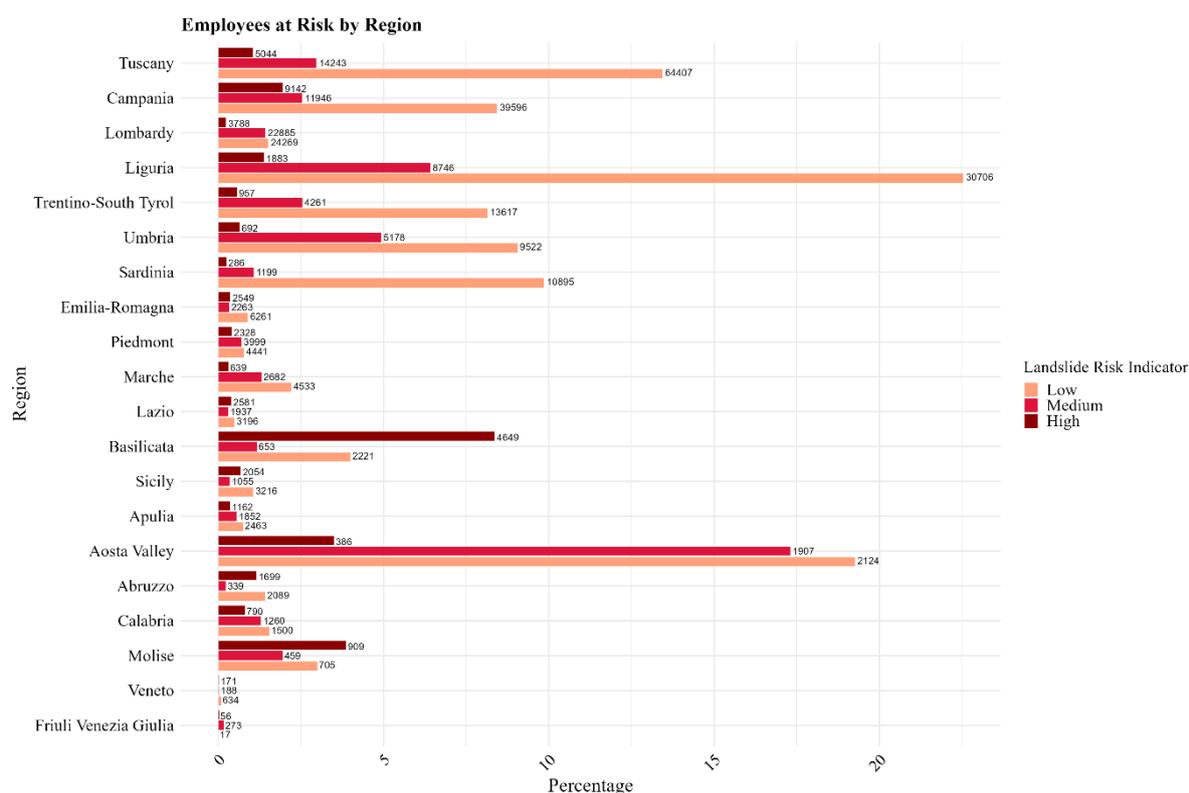
For landslide risk, Tuscany, Campania, and Lombardy have the highest absolute numbers of exposed employees (Figure 6). Aosta Valley has the most significant relative share, with nearly 40 per cent of employees exposed to landslide risk, followed by Liguria (30 per cent). Basilicata has the highest share of employees in the most severe risk area (8.4 per cent).

Figure 5 - Share and number of employees exposed to flood risk by region



Note: absolute numbers are shown near the bars, while shares are along the horizontal axis.

Figure 6 - Share and number of employees exposed to landslides risk by region



Note: absolute numbers are shown near the bars, while shares are along the horizontal axis.

5.2 Physical-Risk Adjusted PD

We now assess the impact of HG risk on firms' creditworthiness using the S-ICAS model, focusing on the financial consequences of expected losses due to floods and landslides. The analysis quantifies physical risk by computing the expected loss associated with these hazards and evaluating their effect on firms' financial health. Our approach allows us to derive risk-adjusted financial statements, incorporating the impact of HG risk into both income statement and balance sheet figures (see Section 4.2).

A key finding is that when accounting for all local units instead of the headquarters only, the total expected revenue loss due to HG risk amounts to €3.5 billion, of which €3 billion stems from flood risk and €0.5 billion from landslide risk. In contrast, considering the headquarters only, the estimated total revenue expected loss is nearly €3 billion. This adjustment translates into an average HG risk-adjusted revenue loss of -0.2 per cent per firm, compared to -0.1 per cent when focusing solely on headquarters (Equation 1). On the asset side, the most significant loss occurs in PPEs, with an expected value reduction of €1.37 billion, of which €1.20 billion is due to floods. Similarly, WIs register an expected loss of nearly €0.65 billion. On average, PPEs and WIs experience value reductions of -0.2 per cent, respectively. These results underscore the material financial impact of HG risk.

With S-ICAS, we convert the risk-adjusted financial statements into physical-risk adjusted PDs. Hence, we examine the breakdown of PD changes of firms overall and across HG risk indicator (Table 9), NACE

sectors (Table 10), size (Table 11) and region (Table 12) analysing ‘Migrated Firms’ or ‘Stable Firms’, along with their respective percentage shares and average PD increments in basis point (bp).

We find that approximately 38 per cent of firms experience an increase in their PD, with an average PD deterioration of 1 bp (Table 9 – Panel A). This relatively modest PD increase is primarily driven by the high concentration of firms in risk category 0, which remains unaffected by any PD changes (Table 9 – Panel B). However, the extent of the average PD deterioration intensifies as firms are exposed to higher risk level in the baseline scenario. In the highest risk category, the average PD increase reaches 9 bp, significantly exceeding the overall average PD changes and those observed across NACE sectors (Table 10) and firm size categories (Table 11). However, if high-impact HG events become more frequent, PD deterioration would intensify, particularly for firms located in the most exposed areas. When we calculate the probability of HG events using the average of the interval bounds and the upper bound (see Table D8), PD increases double or even triple compared to the baseline with an average PD increase of 32 bp for firms in the highest risk category (Table 9 – Panel B). This highlights that, if the frequency and severity of extreme events continue to rise as expected (Emambakhsh *et al.*, 2023), the economic impact could be substantial. In 2025, a year characterised by extreme climate events, the estimated total losses from floods in Italian regions are around 4.6€ billion, expected to rise to 14.2€ billion in 2029. This is equivalent to 0.23 per cent of national GVA in 2025 and 0.72 per cent in 2029 (Usman *et al.*, 2025).

Table 9 - 1-year change in probability of default by HG risk indicator

	Firms (#)	Firms (%)	Average PD increments (bp)			
			Baseline	Lower Bound	Average	Upper Bound
Panel A: Firms						
Total	366,799		1.0	0.6	1.7	2.8
Panel B: HG risk indicator - Max level						
0	227,591	62.1	0.0	0.0	0.0	0.0
Low	61,520	16.8	0.9	0.7	1.0	1.4
Medium	54,864	14.9	1.8	1.1	2.5	3.8
High	22,824	6.2	9.1	4.4	18.9	32.0

Trade, and Manufacturing sectors dominate in terms of PD changes (8.5 per cent and 8.1 per cent, respectively). Specifically, these sectors exhibit the highest absolute numbers of firms experiencing PD changes (31,342 and 29,539 firms, respectively).

Looking at the shares of firms changed against firms unchanged within each sector, Mining and Hosting services show a notable proportion of firms experiencing changes within the sector (41.4 per cent and 40.9 per cent, respectively). These figures are above the overall average increase of 38.6 per cent, indicating that these sectors are particularly sensitive to risk-related adjustments. Conversely,

Construction, and Health services display the highest proportion of firms remaining unchanged. The highest average PD increments are observed in Agriculture and Transportation (1.9 bp), followed by Hosting services (1.3 bp). Whereas Real Estate and Waste management exhibit lower average PD variations (0.6 bp). Sectors Trade and Manufacturing stand out for having a higher proportion of firms with PD changes and relatively higher average PD variations.

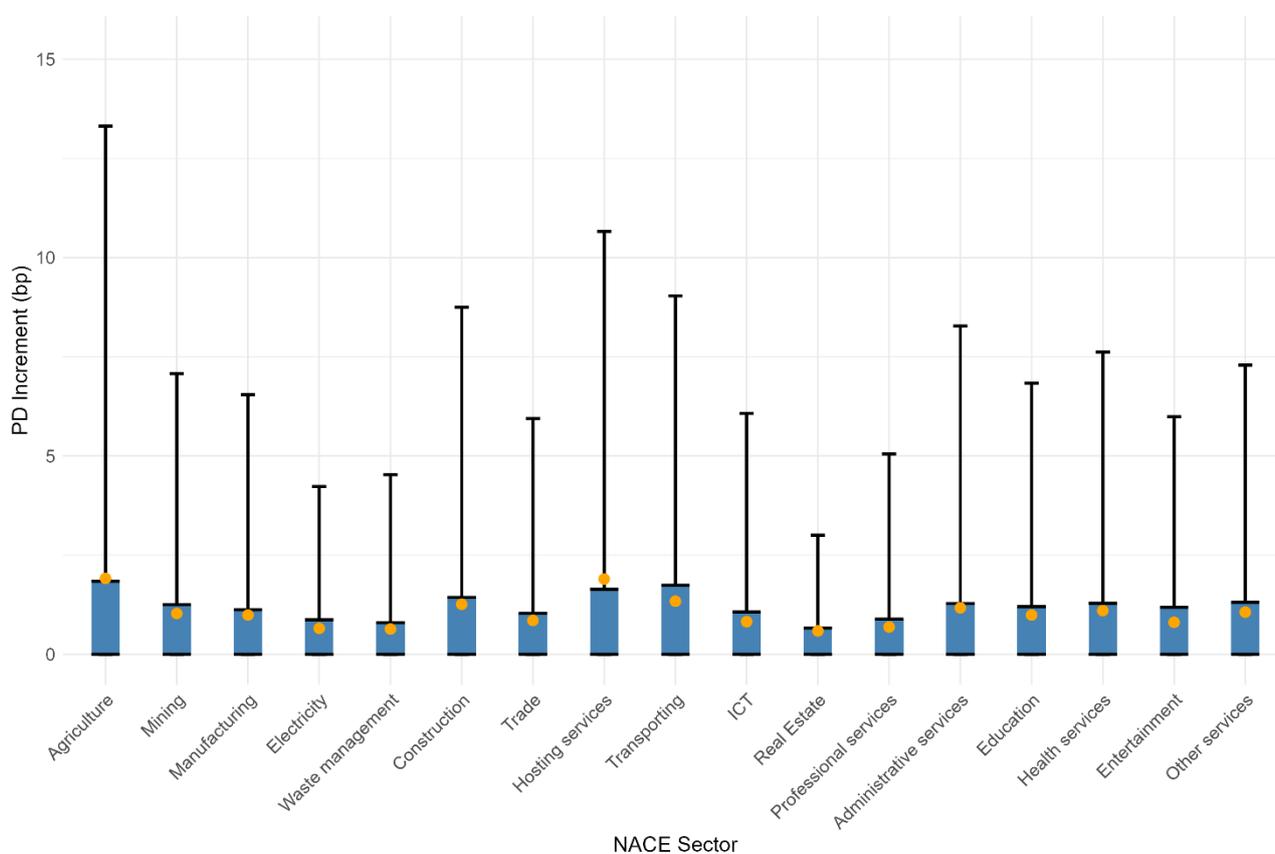
Table 10 - 1-year change in probability of default by NACE sector

NACE Sector	Migrated (# of firms)	Migrated (% total)	Migrated (% sector)	Stable (# firms)	Stable (% total)	Stable (% sector)	Average PD increment (bp)
Agriculture	2,724	0.7	37.6	4,517	1.2	62.4	1.9
Mining	342	0.1	41.4	485	0.1	58.6	1.0
Manufacturing	29,539	8.1	38.8	46,564	12.7	61.2	1.0
Electricity	1,542	0.4	39.7	2,339	0.6	60.3	0.7
Waste management	1,253	0.3	37.4	2,098	0.6	62.6	0.6
Construction	18,012	4.9	34.2	34,594	9.4	65.8	1.3
Trade	31,342	8.5	39.7	47,517	13.0	60.3	0.9
Hosting services	6,614	1.8	40.5	9,708	2.6	59.5	1.9
Transporting	11,188	3.1	40.9	16,161	4.4	59.1	1.3
ICT	4,400	1.2	38.4	7,053	1.9	61.6	0.8
Real Estate	14,390	3.9	35.9	25,747	7.0	64.1	0.6
Professional services	6,195	1.7	37.1	10,490	2.9	62.9	0.7
Administrative services	4,601	1.3	38.9	7,214	2.0	61.1	1.2
Education	853	0.2	40.0	1,279	0.3	60.0	1.0
Health services	3,248	0.9	35.8	5,832	1.6	64.2	1.1
Entertainment	2,116	0.6	41.0	3,042	0.8	59.0	0.8
Other services	1,482	0.4	39.0	2,318	0.6	61.0	1.1

Note: Variations with respect to all firms and within the sector.

Figure 7 illustrates the range (black whiskers) and the average PD increase (orange dot) in bp for firms, categorized by their respective NACE sectors. This figure shows the heterogeneous distribution of PD increments, revealing that some sectors are significantly more exposed to physical risk than others. Among the sectors, Agriculture emerges as the most vulnerable, exhibiting both the highest average PD increase and the largest peak increment, reaching approximately 13 bp. This is followed by Transportation, with a peak of nearly 11 bp, and Construction, where the PD increase reaches 9 bp.

Figure 7 - 1-year probability of default sensitivity to physical risk by NACE sector



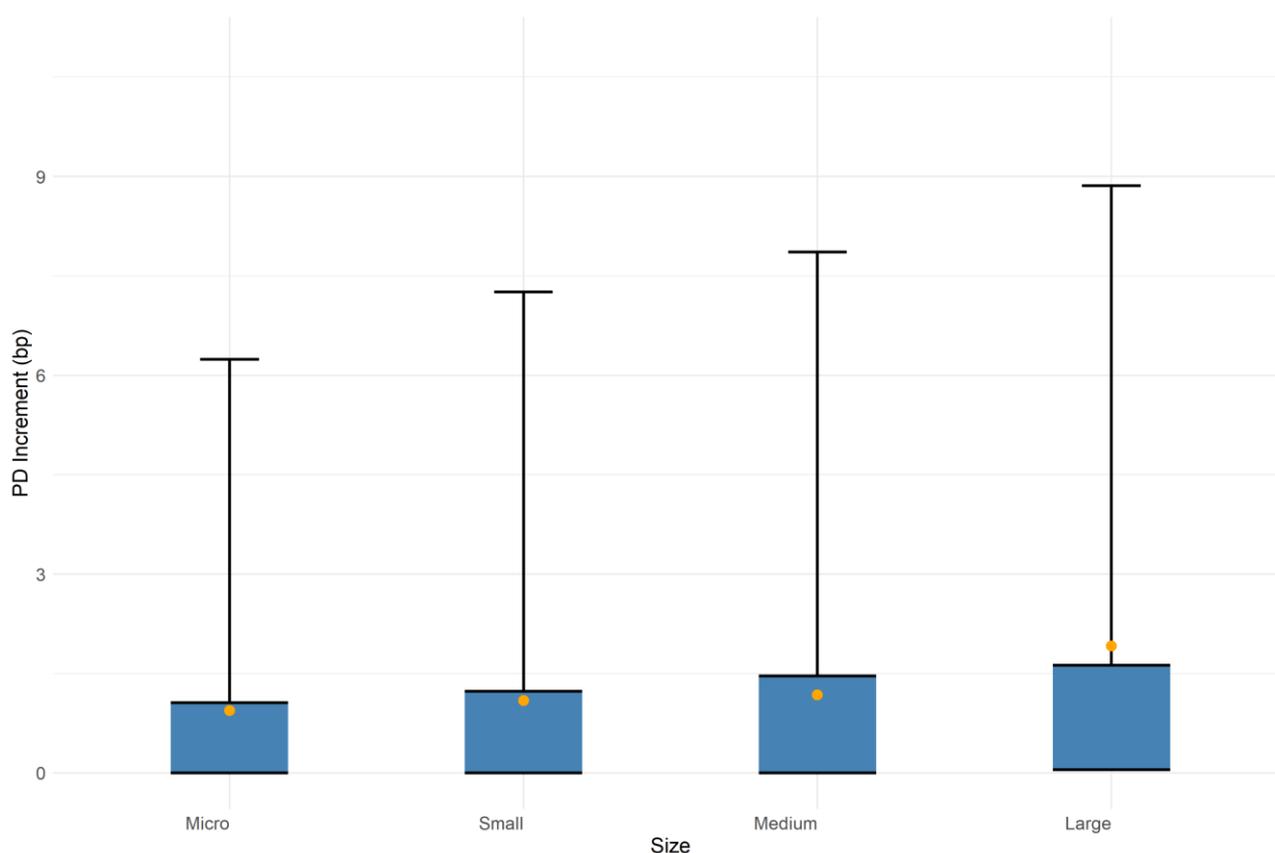
Note: The figure presents a box plot illustrating PD increments in bp across different NACE sectors. The black whiskers represent the variation range, covering the 50th to the 97.5th percentile, while the box spans from the 50th to the 90th percentile. This design provides a more accurate representation of PD increments, given that the median value is 0, effectively capturing the upper tail of the distribution.

As to firm size (Table 11), micro firms exhibit the highest change in absolute terms, however large firms vary the most in PD changes within their size category, with 59.4 per cent of firms affected and 40.6 per cent remaining unchanged. Micro firms have the lowest proportion of PD changes (36.0 per cent) within their size class, indicating greater stability. Similarly, small firms exhibit a slightly higher rate of PD changes (39.3 per cent) than micro firms. Medium firms fall between these extremes, with 45.8 per cent of firms experiencing changes. Besides, large firms display the highest average PD variation (1.9 bp), followed by medium (1.2 bp), lastly small and micro firms (1.1 bp and 0.9 bp, respectively). Figure 8 provides graphical insights into the distribution of PD increments and average PD changes by firm size. A visual inspection reveals a linear relationship between firm size and PD increments, suggesting that larger firms experience greater PD deterioration. This trend seems attributable to the fact that large firms with many branches are more likely to be exposed to HG risk (as in Loberto and Russo, 2024a).

Table 11 - 1-year change in probability of default by size

Size	Migrated (# of firms)	Migrated (% total)	Migrated (% size)	Stable (# firms)	Stable (% total)	Stable (% size)	Average PD increment (bp)
Large	3,083	0.8	59.4	2,108	0.6	40.6	1.9
Medium	12,684	3.5	45.8	14,993	4.1	54.2	1.2
Small	46,104	12.6	39.3	71,179	19.4	60.7	1.1
Micro	77,970	21.3	36.0	138,668	37.8	64.0	0.9

Figure 8 - 1-year probability of default sensitivity to physical risk by firm size



Note: The figure presents a box plot illustrating PD increments in bp across different NACE sectors. The black whiskers represent the variation range, covering the 50th to the 97.5th percentile, while the box spans from the 50th to the 90th percentile. This design provides a more accurate representation of PD increments, given that the median value is 0, effectively capturing the upper tail of the distribution.

Finally, the results at regional level²⁹ shows that Emilia Romagna, Tuscany and Lombardy are the regions with the highest share of firms with PD changes are, consistently with exposure at local units and employees level: Emilia Romagna has 7.2 per cent of firms with a PD deterioration, followed by Tuscany (7.1 per cent) and Lombardy (4.9).

²⁹ We refer to the headquarter location for summarising the results.

In relative terms, for four regions in the Centre-North of Italy the percentage of firms experiencing PD changes is above 70 per cent. Conversely, two regions in the South exhibit the lowest percentage of firms changed (14 per cent).

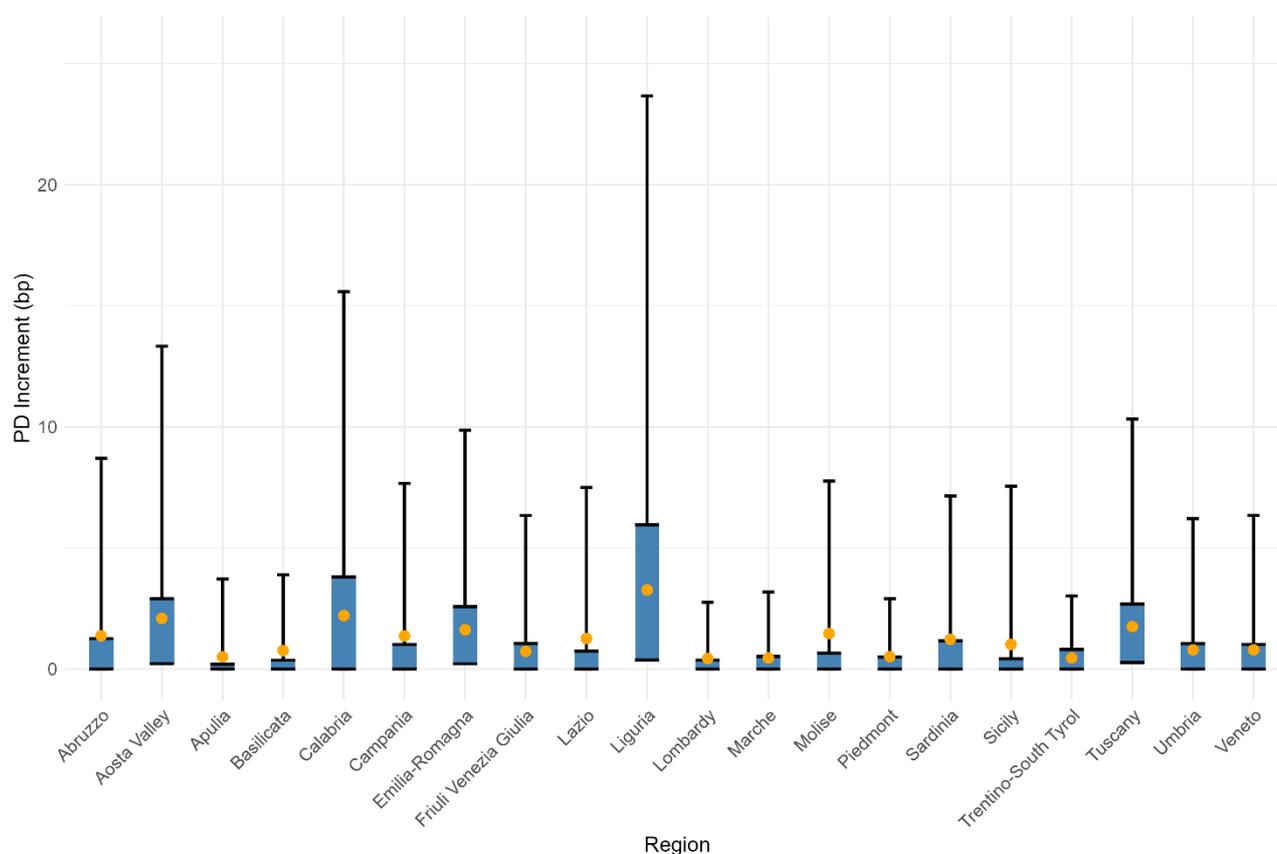
In terms of average PD increments, Liguria is the most exposed region with a PD increase of 3.2 bp, followed by Aosta Valley and Calabria with average PD increments above 2 bp. Figure 9 provides graphical details about the distribution of PD increments and the average increases by region, highlighting that Liguria, Calabria and Aosta Valley also experience the highest PD increment peaks, reaching 24, 16 and 13 bp, respectively. These findings underscore the regional disparities and vulnerability of firms operating in these areas.

Table 12 - 1-year change in probability of default by region

Region	Migrated (# of firms)	Migrated (% total)	Migrated (% region)	Stable (# firms)	Stable (% total)	Stable (% region)	Average PD increment (bp)
Abruzzo	2,724	0.7	35.4	4,964	1.4	64.6	1.4
Aosta Valley	532	0.2	74.9	178	0.1	25.1	2.1
Apulia	2,492	0.7	14.4	14,790	4.0	85.6	0.5
Basilicata	522	0.1	19.7	2,123	0.6	80.3	0.8
Calabria	2,282	0.6	35.4	4,171	1.1	64.6	2.2
Campania	8,966	2.4	31.3	19,675	5.4	68.7	1.4
Emilia Romagna	26,286	7.2	78.4	7,253	2.0	21.6	1.6
Friuli Venezia Giulia	2,702	0.7	39.1	4,206	1.2	60.9	0.7
Lazio	8,742	2.4	23.6	28,316	7.7	76.4	1.3
Liguria	5,822	1.6	82.8	1,212	0.3	17.2	3.3
Lombardy	18,053	4.9	23.1	60,003	16.4	76.9	0.4
Marche	3,220	0.9	28.3	8,154	2.2	71.7	0.5
Molise	322	0.1	22.0	1,143	0.3	78.0	1.5
Piedmont	6,491	1.8	29.6	15,478	4.2	70.5	0.5
Sardinia	2,663	0.7	43.6	3,442	0.9	56.4	1.2
Sicily	2,720	0.7	14.1	16,556	4.5	85.9	1.0
Tuscany	25,827	7.0	89.5	3,032	0.8	10.5	1.8
Trentino-South Tyrol	3,042	0.8	37.5	5,061	1.4	62.5	0.5
Umbria	2,255	0.6	39.7	3,431	0.9	60.3	0.8
Veneto	13,374	3.7	37.9	21,918	6.0	62.1	0.8

Note: Variations with respect to all firms and within the region.

Figure 9 - 1-year probability of default sensitivity to physical risk by region



Note: The figure presents a box plot illustrating PD increments in bp across different NACE sectors. The black whiskers represent the variation range, covering the 50th to the 97.5th percentile, while the box spans from the 50th to the 90th percentile. This design provides a more accurate representation of PD increments, given that the median value is 0, effectively capturing the upper tail of the distribution.

As a whole, the results of our analysis reveal a significant heterogeneity across sectors in terms of PD changes. Sectors with a larger number of firms tend to have a balanced distribution between firms with and without PD changes, while some smaller sectors exhibit a higher relative proportion of firms experiencing a change. Besides, the analysis reveals a clear relationship between firm size and risk. Larger firms face higher risk, as shown by the greater proportion of PD changes within their size category and higher average PD increment. This finding is consistent with the fact that large firms operate with multi-branches. The regional analysis discloses significant disparities in PD changes and stability. Tuscany, Emilia-Romagna, Liguria and Aosta Valley exhibit the largest proportion of firms experiencing PD changes (as expected from the exposure analysis in Section 5.1) whereas Liguria, Aosta Valley and Calabria exhibit the highest increase in the average PD.

Finally, to verify the robustness of our results, we repeat the analysis using a different geo-locating server (see Appendix D for the results) and test the correlation between the difference in physical-risk adjusted PDs and baseline PDs and the HG risk discrete indicator. The Spearman correlation test shows 89 per cent

correlation, which is statistically significant at the 1 per cent level. This is consistent with ex-ante expectations: a higher risk level corresponds to higher PD deterioration.

6. Further results

6.1 The impact on collateral in monetary policy operations

The Banca d'Italia ICAS model plays an important role in evaluating collateral used in monetary policy operations. Several banks rely on BI-ICAS to assess the quality of the collateral they pledge when accessing Eurosystem refinancing operations. In these operations, the Eurosystem accepts both marketable assets and credit claims. These claims typically arise from loans granted by banks to the public sector, corporates, and small- and medium-sized enterprises. Physical risk could impair the banks' ability to pledge collateral, potentially reducing their refinancing capacity and affecting liquidity management.

To gauge the impact of changes of firms' creditworthiness on collateral value we analyse shifts within the harmonised rating scale of the ECAF: the CQS. Under this framework,³⁰ one-year PD ranges define the CQS classes, from the safest (CQS1and2,) to the riskiest (CQS 8. See Table 13). In the ordinary ECAF framework, only assets rated at least CQS 3 are eligible as collateral. By contrast, in the Additional Credit Claims scheme (ACCs), individual loans up to CQS 5 are eligible, while pools of credits can include loans up to CQS 8.³¹ Based on the CQS rating, the Eurosystem applies a haircut to the collateral value; a bank's borrowing capacity is determined by the net collateral value after this reduction. As of December 2023, BI-ICAS had evaluated almost 27 per cent of the credit claims pledged by Italian banks as collateral in monetary policy operations (both individual loans and pools), with an outstanding amount equal to €29 billion.³²

Table 13 – ECAF rating scale

(percentage values)

Minimum PD	Maximum PD	CQS
0	0.1	CQS1and2
0.1	0.4	CQS3
0.4	1	CQS4
1	1.5	CQS5
1.5	3	CQS6
3	5	CQS7
5	100	CQS8
100	100	Default

³⁰ Article 82 of Guideline ECB/2014/30.

³¹ ACCs are a temporarily extension of the types of assets eligible as collateral to ensure that banks have full access to central bank liquidity, even in adverse economic condition. ACCs are credit claims that do not fulfil all the eligibility criteria applicable under the general collateral framework, as lowering credit quality. Italian ACCs is regulated by "Condizioni generali relative alle garanzie 2024.1".

³² Given the prioritization of ICAS rating, we expect this percentage to increase (Columba, Orsini, & Tranquillo, 2024).

An examination of transition dynamics across risk classes shows that the safest CQS classes are largely stable (Table 14). CQS1and2, the most stable classes, experience a minor outflow of 101 firms (-0.5 per cent), while CQS3 loses 177 firms (-0.3 per cent). All firms that shift away from CQS 3 are no more eligible as collateral for monetary policy operations in the ordinary ECAF framework. Middle classes (CQS 4 – CQS6) shifts are negligible, indicating strong stability within this segment. CQS7 and CQS8 experience small increases, gaining 128 firms (+0.3 per cent) and 236 firms (+0.4 per cent), respectively. These results suggest that, in percentage terms, the deteriorations in PD are more numerous in the lower quality classes.

Table 14 – 1-year change in Eurosystem credit risk quality

CQS	Firms (#)	Firms (%)	Firms Stressed (#)	Firms Stressed (%)	Delta (#)	Delta (%)	Average PD increments (bp)
CQS1and2	19,208	5.2	19,107	5.2	-101	-0.5	0.0
CQS3	63,172	17.2	62,997	17.2	-175	-0.3	0.1
CQS4	72,701	19.8	72,708	19.8	7	0.0	0.3
CQS5	32,612	8.9	32,551	8.9	-61	-0.2	0.6
CQS6	64,981	17.7	64,947	17.7	-34	-0.1	0.9
CQS7	48,633	13.3	48,761	13.3	128	0.3	1.3
CQS8	65,241	17.8	65,477	17.9	236	0.4	3.2

Overall, the magnitude of these shifts is minimal. Although physical risks lead to a deterioration in PD for about 38 per cent of cases, the direct impact on credit quality is limited, with only 0.4 per cent of firms experiencing a downgrade in their CQS rating (Table 15). The stability in the middle and high-quality classes, alongside the modest increase in the riskiest classes, produces a marginal deterioration in the value of collateral of 0.4 per cent (individual loans and pools). Thus, the overall effect on collateral value is economically insignificant.

Table 15 – Overall migration in 1-year default probability and in credit quality class

Variation	Migrated (#)	Migrated (%)	Stable (#)	Stable (%)	Average PD increment (bp)
PD	139,841	38.1	226,958	61.9	1.02
CQS	1,571	0.4	365,228	99.6	1.02

6.2 Does insurance matter?

Many studies in this field do not take into account the role of insurance against natural hazards and mitigation policies due to data limitations. In Italy, insurance against natural hazards will become mandatory for all firms across all sectors (except agriculture) seeking access to public restoration funds in case of disasters (DL 202/2024).

The new law requires that insurance policies cover at least 85 per cent of damages to plants, buildings, and land, with insurance companies mandated to immediately pay out at least 30 per cent of the insured amount upon damage assessment (Law 213/2023).

According to the INVIND survey,³³ 68 per cent of Italian firms currently hold insurance against natural hazards. Among those without coverage, the primary obstacle is the high cost of insurance premiums (Gallo *et al.*, 2022). Despite this relatively high reported coverage rate, European data presents a stark contrast, indicating that only 5 per cent of potential losses incurred by Italian firms are actually insured (European Environment Agency, 2023). This discrepancy suggests that while firms may hold some level of coverage, this is generally insufficient to offset the financial risks associated with extreme events.

Banca d'Italia carried out a survey in 2024, designed for the BI-ICAS framework. This initiative aimed at the collection of granular data on firms' greenhouse gas emissions, energy consumption, financial exposure to climate-related events, and insurance coverage, providing insights into their vulnerability and risk mitigation strategies. This allows us to extend our analysis by examining the mitigation effects of insurance coverage for firms that responded to the survey.³⁴

Since insurance premiums are recorded under "Service Costs" in the 2023 income statement, no additional expense is considered. This is important, as purely quantitative credit scoring models do not account for insurance coverage. Moreover, the insurance premium is typically treated as an operational cost, and the insurance financial benefits are only recognised in the financial statement when a covered adverse event occurs. As a result, a firm that insures against HG risks may be assessed with a higher PD than are otherwise identical firm (i.e. one with the same financial statement) that chooses not to insure. Our methodology, which incorporates a HG risk-adjusted financial statement, accounts for the potential financial benefit of insurance against HG risks.

Regarding insurance coverage for potential damages, we make the following assumptions based on the upcoming regulation (Law 213/2023):

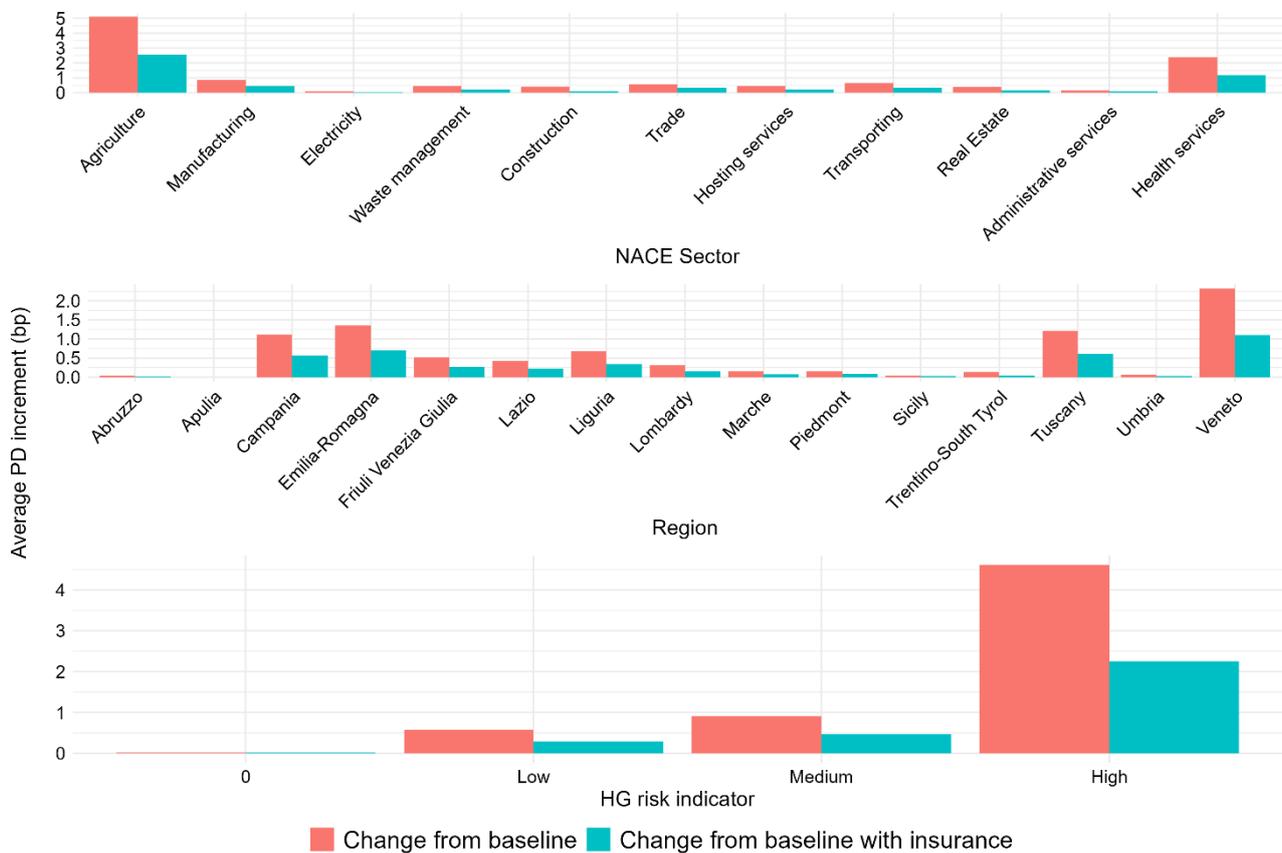
³³ The survey conducted by the Bank of Italy annually collects information on investments, revenue, employment, and other economic variables of Italian industrial and service enterprises with at least 20 employees.

³⁴ This extension applies to 228 firms only. While not fully representative of the S-ICAS sample, it serves as a valuable starting point for assessing the potential impact of insurance coverage.

1. **Reduced Business Disruption:** As insurers must immediately reimburse 30 per cent of damages, we assume business disruption time is halved following a HG event (see Section 4.2).
2. **Asset Value Adjustment:** Since insurance covers at least 85 per cent of damages to plants, buildings, and land, we reduce the PPE's value by 15 per cent only in case of an HG event. This adjustment does not apply to WI.

Our findings indicate that insurance coverage significantly reduces the PD increase following HG events—by nearly half, regardless of NACE sector, region, or HG intensity indicator (Figure 10). This result is noteworthy, as banks currently do not differentiate between firms with or without insurance coverage (Gallo *et al.*, 2024).

Figure 10 - Average PD increase with and without insurance coverage



7. Conclusion

This paper advances the assessment of credit risk for non-financial firms by integrating climate change-related physical risks into firms' PD estimation. We focus on HG risk (flood and landslide), which is particularly relevant in Italy due to its distinctive geographical characteristics. Our methodology leverages ISPRA's mosaic risk map, which provides granular flood and landslide data, to estimate physical risks at the local unit level. To evaluate the impact of physical risk on firms' creditworthiness, we examine how damages and business disruptions caused by HG events affect firms' financial statements. Our

methodology addresses a critical gap in previous studies by incorporating the full geographic exposure of firms' operations.

Our findings show that nearly 38 per cent of Italian firms are exposed to HG risks when accounting for all local unit. In most cases, floods and landslides have limited effect on the one-year PD with an average PD deterioration of about 1 bp and a small number of rating migration. Nevertheless, firms located in high-risk areas, classified in the worst category of our risk indicator, may face significant financial losses, with an average PD deterioration of 9 bp, far beyond the overall average. The impact on collateral value is economically negligible: the deterioration in the value of collateral is of 0.37 per cent (both individual loans and pools).

Insurance coverage emerges as a key risk mitigation factor. Our results indicate that, for a subsample of firms, insurance against natural hazard can reduce the average PD deterioration by nearly 50 per cent. This finding is particularly noteworthy given available evidence that banks usually do not differentiate between firms insured or uninsured. A widespread presence of insurance coverage could potentially lower borrowing costs, making bank loans more affordable for insured firms, in addition to contributing to the stability of the financial system.

Our methodology, based on expected loss estimation, differs from traditional stress testing and scenario-based approaches, which often rely on assumptions about extreme events that have yet to materialize. By combining the granularity of physical risk exposure with a probabilistic framework, our approach offers a robust and flexible model that can be integrated into credit risk assessment frameworks, including ICAS and IRB systems. Such integration can improve PD forecasting accuracy, helping all type of lenders to better manage risks associated with HG events.

However, it is important to note that our analysis relies on ISPRA hazard maps, whose probabilities are derived from historical observations. Climate change is driving a substantial increase in the frequency of extreme natural events globally, with particularly strong effects in Italy. Therefore, our results should be interpreted as reflecting an average historical scenario. In the absence of targeted policy interventions, the frequency and severity of extreme events are expected to rise further, triggering more significant economic impacts for firms located in highly exposed areas. If we consider the current worst scenario, the PD deterioration is more than three times higher than in the baseline scenario, with an average PD increase of 32 bp for firms in the highest risk category.

Moreover, ISPRA mosaic risk maps are subject to the typical uncertainties of hydrogeological modelling, but ISPRA mosaic is embedded within the regulatory framework³⁵ and serves as the official tool for hydraulic risk management and assessment at both national and European levels. We acknowledge these limitations to enhance transparency and lay the groundwork for future research, such as incorporating

³⁵ EU Floods Directive (2007/60/EC)

flood depth data or confidence bands, when available, and industrial building characteristics to enhance vulnerability assessment. This would lead to more accurate expected loss estimations along with a broader dataset on firms' insurance coverage, which will become mandatory for all firms in Italy.

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Appendix A

Table A.1 reports the NACE sector classification, with letter and economic activity denomination.

Table A.1 - List of NACE sectors, letter and activities denomination.

Letter	Short Name	Long Name
A	Agriculture	Agriculture, forestry and fishing
B	Mining	Mining and quarrying
C	Manufacturing	Manufacturing
D	Electricity	Electricity, gas, steam and air conditioning supply
E	Waste management	Water supply; sewerage; waste management and remediation activities
F	Construction	Construction
G	Trade	Wholesale and retail trade
H	Hosting services	Accommodation and food service activities
I	Transporting	Transporting and storage
J	ICT	Information and communication
K	Financial Services	Financial and insurance activities
L	Real Estate	Real estate activities
M	Professional services	Professional, scientific and technical activities
N	Administrative services	Administrative and support service activities
P	Education	Education
Q	Health services	Human health and social work activities
R	Entertainment	Arts, entertainment and recreation
S	Other services	Other services activities

Appendix B

We estimate variable costs and personnel costs elasticity at NACE sector level. For each sector s , we use financial statement data for limited firms from 2010 to 2018 to estimate $\eta_{j,s}$ with $j = VC, LC$ using the following equation (De Socio, et al., 2020):

$$\log y_{i,t} = \eta_{j,s} \log r_{i,t} + \gamma X_{i,t-1} + \theta_t + \xi_i + \varepsilon_{i,t} \quad (1.B)$$

Where s is the i -th firm's sector, $r_{i,t}$ is the i -th firm's revenues, $X_{i,t-1}$ is a vector of control variables including total assets and net income, θ_t and ξ_i are time and firm fixed effect. We exclude from the sample firms whose total assets and total revenues are less than 500.000 euros. Table B.1 reports the estimated elasticities.

Table B.1 – Estimated elasticity for NACE sector

NACE	Variable Cost	Personnel Cost
A	0.64	0.23
B	0.75	0.3
C	0.78	0.25
D	0.87	0.12
E	0.77	0.27
F	0.68	0.21
G	0.92	0.1
H	0.68	0.25
I	0.7	0.26
J	0.63	0.24
K	0.72	0.21
L	0.62	0.22
M	0.71	0.21
N	0.64	0.28
P	0.66	0.22
Q	0.55	0.33
R	0.71	0.19
S	0.62	0.28

Note: authors' estimates based on Cerved data. Some companies that have a special format for financial statements ("real estate companies") are excluded.

Appendix C

The ESRI geocoding system involves a multi-layered process designed to maximize accuracy. Initially, addresses are parsed and standardized according to regional norms, ensuring consistency in format. This involves resolving inconsistencies in address notation, such as abbreviations, punctuation, and formatting conventions, to align with the input requirements of the ESRI API. Address components, such as street names, house numbers, postal codes, and administrative divisions, are segmented and validated against reference datasets. The pre-processing step is crucial for improving the likelihood of obtaining accurate matches from the geocoding service.

Each pre-processed address is then sent to the ESRI API, which generates a list of potential candidate locations. The API evaluates these candidates based on their similarity to the input address and assigns a confidence score to each match. The algorithm selects the candidate location with the highest score, provided it meets or exceeds a confidence threshold of 90 per cent. Addresses failing to meet this threshold are flagged for manual review to ensure that no critical data are omitted. To further enhance precision, we implement a validation mechanism where a subset of geocoded addresses is cross-referenced with manually verified locations and output from alternative providers. Specifically, we analyse a subset of enterprises using results from Nominatim (OpenStreetMap) and Google Maps, comparing their geocoding accuracy with that of the ESRI system. This analysis informs the empirical justification for the 90 per cent threshold, demonstrating its efficacy in balancing precision and recall while minimizing false positives.

The algorithm developed for this process incorporates additional safeguards to ensure robustness. It supports batch processing, allowing multiple addresses to be geocoded simultaneously, and employs parallelization techniques to optimize computational efficiency. The standardized output format provided by the ESRI API ensures consistent representation of address components, facilitating seamless integration with other datasets, such as the ISPRA mosaic risk maps. These standardized data form the basis for mapping firms' local units to their respective hydrogeological risk zones, enhancing the accuracy of physical risk-adjusted PD models.

The decision to set a 90 per cent confidence threshold is informed by an extensive analysis of geocoding results across different providers. By comparing the accuracy of ESRI's results with those from Nominatim and Google Maps on a representative subset of firms, we find that matches below the 90 per cent threshold often lead to incorrect or imprecise geolocations. Conversely, matches meeting or exceeding this threshold consistently align with ground-truth data. This empirical validation underscores the reliability of the ESRI system when operate within these parameters.

The geocoded data serves as a foundation for mapping firms' local units to their respective hydrogeological risk zones, as defined by the ISPRA mosaic risk maps. By ensuring high-precision geocoding, we mitigate the risk of misclassification, thereby enhancing the accuracy of our physical risk-

adjusted PD models. Furthermore, the standardized geocoded data facilitates seamless integration with other geospatial datasets, enabling a comprehensive analysis of risk exposure at both the firm and regional levels.

Building on the geocoded data, the integration process with the ISPRA hydrogeological risk maps establishes a robust link between each local unit and its corresponding hazard zones. The procedure begins by aligning the datasets through the standardization of coordinate reference systems to ensure spatial compatibility. The ISPRA maps, detailed as shapefiles, provide polygons that categorize flood and landslide risks based on factors such as probability and intensity.

A spatial join operation matches the geocoded local unit coordinates to these hazard zones, appending specific risk attributes to each unit. For locations positioned near the boundaries of risk polygons, buffering techniques refine the spatial assignment, ensuring accurate alignment. This process is critical for mitigating errors that may arise from overlapping or closely adjacent zones.

Figure C1 - Italy political map



Appendix D

Robustness checks - OpenStreetMap geolocalisation

We repeat our analysis with OpenStreetMap/Nominatim geolocalisation as consistency check.

Table D1 - Distribution of industrial building per risk category

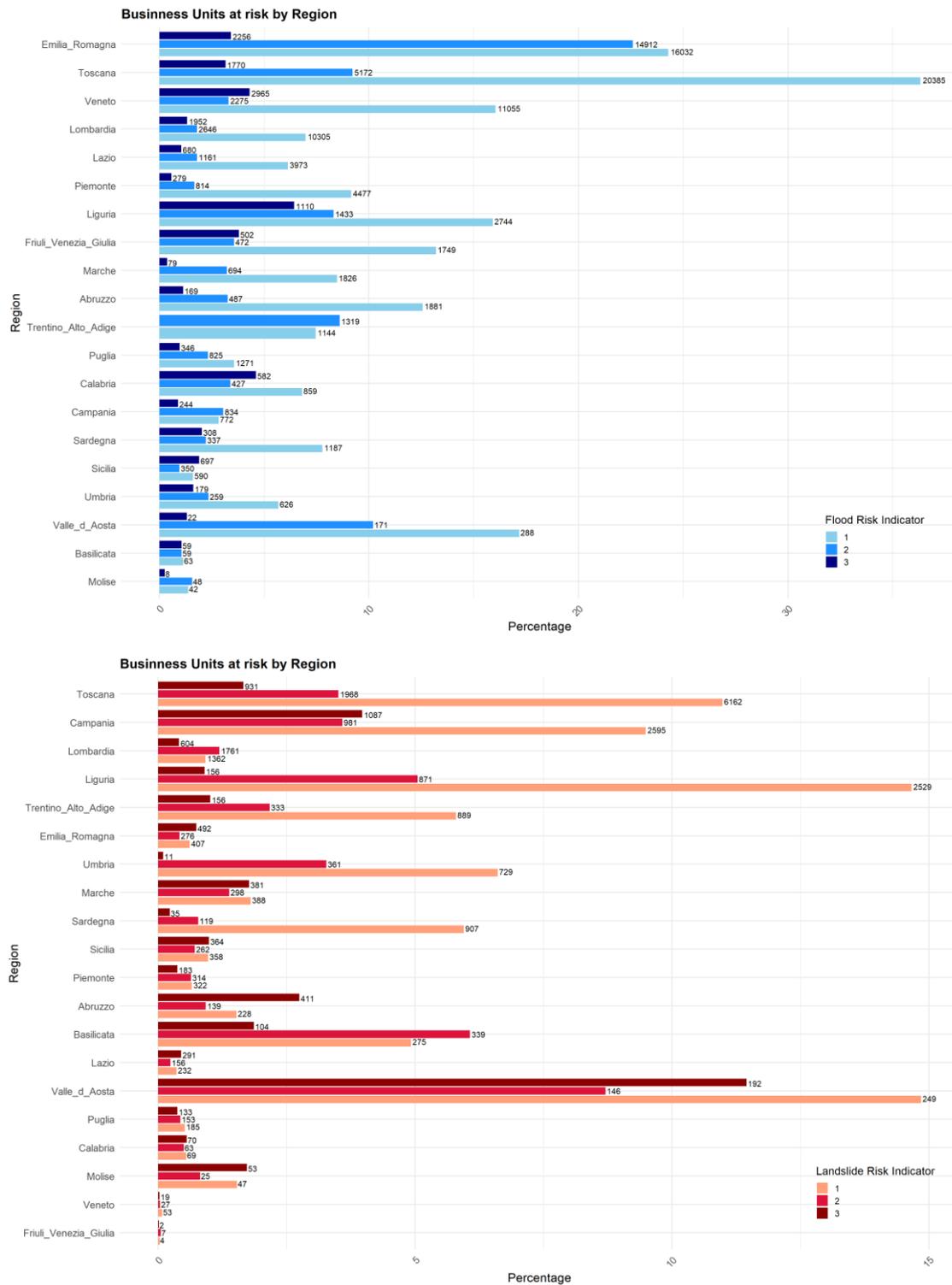
(percentage values)

ISPRA risk category	Office	Plant	Shop	Warehouse	Other	Total
Panel A: Flood						
0	16.42	13.29	20.67	21.33	1.05	72.76
LPH	2.46	2.03	3.38	3.14	0.18	11.19
MPH	2.12	2.05	2.88	3.05	0.21	10.32
HPH	1.20	0.99	1.81	1.63	0.12	5.74
Panel B: Landslide						
0	20.61	16.86	26.39	26.92	1.36	92.15
P1	0.63	0.51	0.93	0.83	0.09	2.99
P2	0.51	0.48	0.77	0.69	0.05	2.51
P3	0.28	0.32	0.41	0.44	0.03	1.49
P4	0.16	0.18	0.23	0.26	0.02	0.86

Table D2 - Discrete risk indicators*(percentage values)*

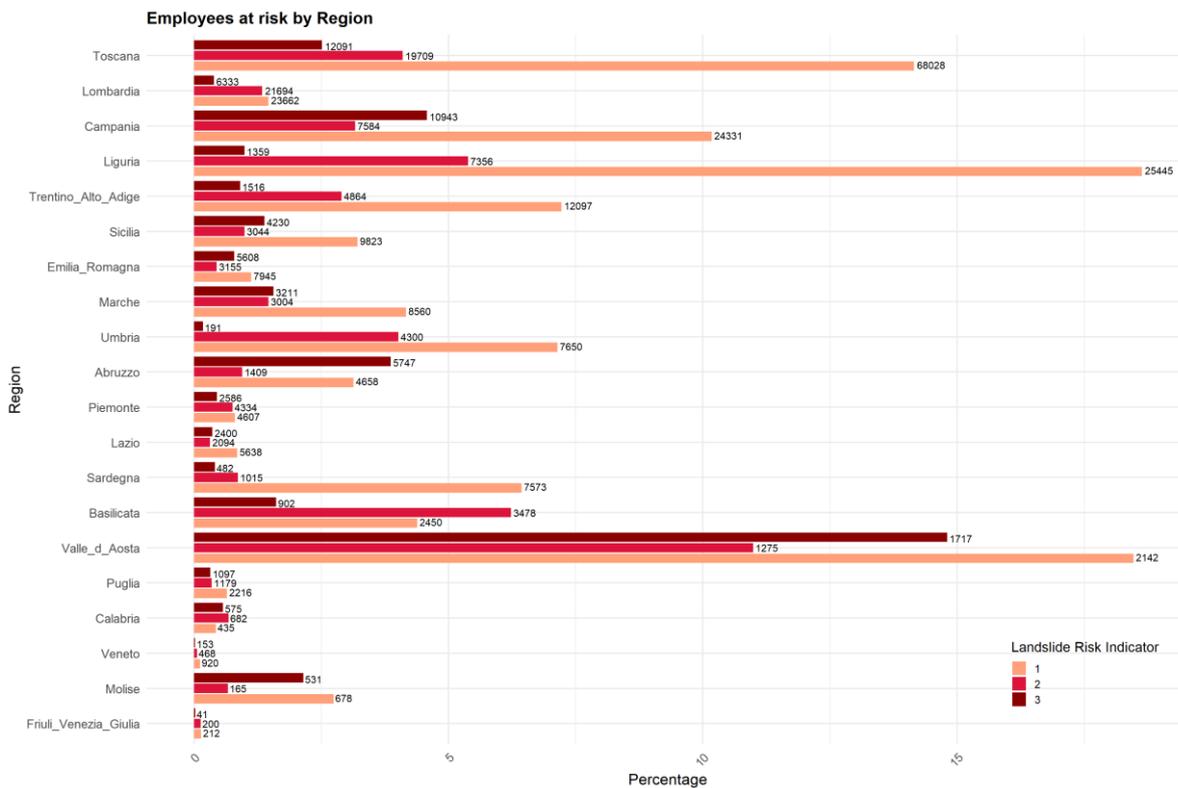
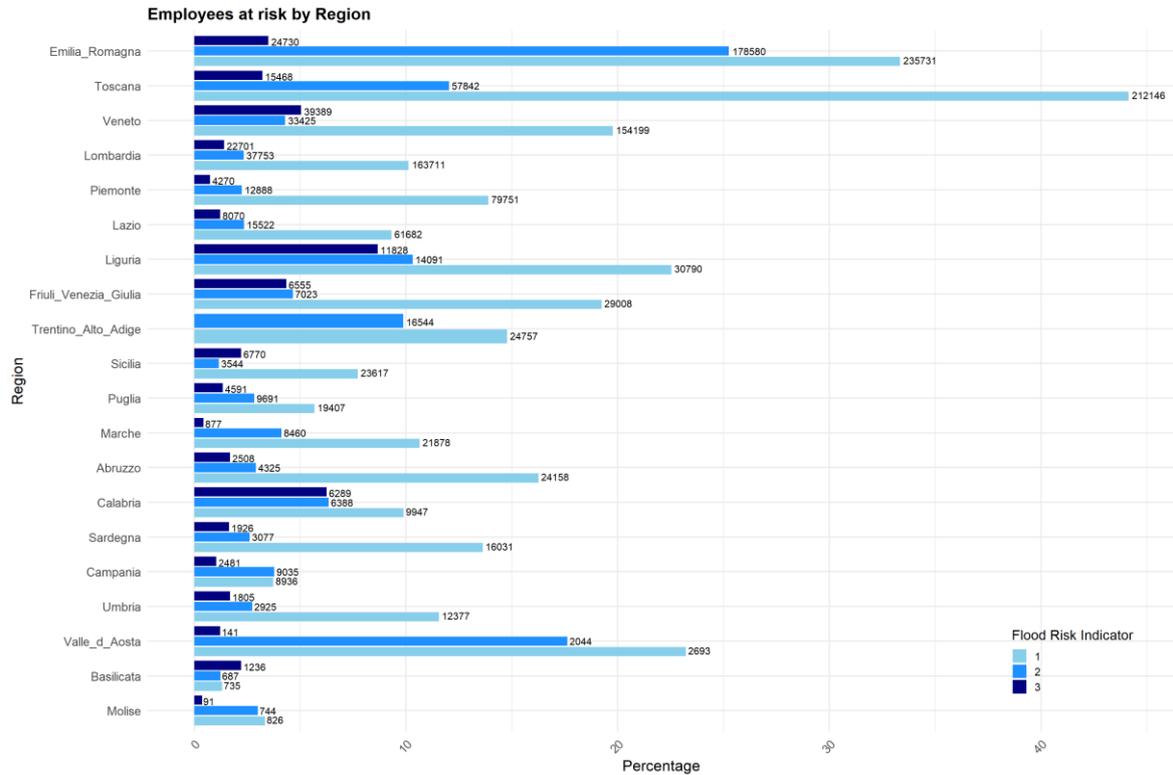
Risk Indicator	Flood (% firms)	Landslide (% firms)	HG (% firms)
Panel A: All local units			
0	70.05	91.59	64.64
1	14.12	3.92	15.57
2	11.07	2.50	13.11
3	4.76	1.99	6.68
Panel B: Only headquarters			
0	73.85	92.69	68.98
1	10.73	2.79	11.79
2	10.09	2.35	11.88
3	5.33	2.17	7.35

Figure D1 – Share and number of exposed local units by region. Flood hazard (upper panel) and landslide hazard (lower panel)



Note: absolute numbers are shown near the bars, while shares are along the horizontal axis. Source: Nominatim/OpenStreetMap geolocalisation server.

Figure D2 - Share and number of exposed employees by region. Flood hazard (upper panel) and landslide hazard (lower panel)



Note: absolute numbers are shown near the bars, while shares are along the horizontal axis. Source: Nominatim/OpenStreetMap geolocalisation server.

Table D3 - 1-year change in probability of default for NACE sectors with respect to all firms and within the sector

NACE Sector	Migrated (# firms)	Migrated (% total)	Migrated (% sector)	Stable (# firms)	Stable (% total)	Stable (% sector)	Average PD increment (bp)
A	2,573	0.7	35.54	4,667	1.27	64.46	1.99
B	302	0.08	36.52	525	0.14	63.48	0.91
C	27,787	7.57	36.47	48,402	13.18	63.53	1.05
D	1,475	0.4	38.03	2,404	0.65	61.97	0.93
E	1,171	0.32	34.92	2,182	0.59	65.08	0.66
F	16,808	4.58	31.94	35,821	9.76	68.06	1.4
G	29,329	7.99	37.13	49,655	13.52	62.87	0.82
H	6,162	1.68	37.72	10,173	2.77	62.28	1.55
I	10,581	2.88	38.64	16,801	4.58	61.36	1.31
J	4,134	1.13	36	7,350	2	64	0.81
L	13,643	3.72	33.99	26,500	7.22	66.01	0.59
M	5,874	1.6	35.17	10,830	2.95	64.83	0.68
N	4,340	1.18	36.69	7,489	2.04	63.31	1.17
P	799	0.22	37.44	1,335	0.36	62.56	0.9
Q	3,139	0.85	34.55	5,946	1.62	65.45	1.15
R	1,976	0.54	38.26	3,188	0.87	61.74	0.87
S	1,417	0.39	37.18	2,394	0.65	62.82	1.11

Table D4 - 1-year change in probability of default for all firms and within size

Size	Migrated (# firms)	Migrated (% total)	Migrated (% size)	Stable (# firms)	Stable (% total)	Stable (% size)	Average PD increment (bp)
Large	2,999	0.82	57.65	2,203	0.6	42.35	2.03
Medium	12,106	3.3	43.68	15,609	4.25	56.32	1.16
Small	43,538	11.86	37.1	73,823	20.11	62.9	1.12
Micro	72,867	19.85	33.6	144,015	39.22	66.4	0.94

Table D5 - 1-year change in probability of default for all firms and within region

Region	Migrated (# firms)	Migrated (% total)	Migrated (% region)	Stable (# firms)	Stable (% total)	Stable (% region)	Average PD increment (bp)
Abruzzo	2,907	0.79	37.84	4,775	1.3	62.16	1.67
Basilicata	834	0.23	31.54	1,810	0.49	68.46	1.06
Calabria	1,859	0.51	28.81	4,593	1.25	71.19	1.49
Campania	5,213	1.42	36.58	9,039	2.46	63.42	2.00
Emilia Romagna	24,932	6.79	74.41	8,576	2.34	25.59	1.64
Friuli Venezia Giulia	2,445	0.67	39.23	3,788	1.03	60.77	0.94
Lazio	7,054	1.92	19.04	29,994	8.17	80.96	1.02
Liguria	5,361	1.46	76.27	1,668	0.45	23.73	2.92
Lombardy	16,720	4.55	21.42	61,340	16.71	78.58	0.54
Marche	3,129	0.85	27.51	8,244	2.25	72.49	0.47
Molise	258	0.07	17.61	1,207	0.33	82.39	0.49
Piedmont	5,788	1.58	26.35	16,181	4.41	73.65	0.49
Puglia	2,887	0.79	15.31	15,971	4.35	84.69	0.48
Sardinia	2,446	0.67	35.06	4,531	1.23	64.94	1.07
Sicily	2,529	0.69	13.12	16,746	4.56	86.88	1.1
Tuscany	25,126	6.84	87.18	3,696	1.01	12.82	1.88
Trentino-Alto Adige	2,933	0.8	36.15	5,180	1.41	63.85	0.51
Umbria	1,806	0.49	31.8	3,874	1.06	68.2	0.62
Aosta Valley	483	0.13	68.41	223	0.06	31.59	4.99
Veneto	13,330	3.63	37.68	22,051	6.01	62.32	0.91

Table D6 – 1-year change in ICAS and Eurosystem credit risk quality

	Stable (#)	Stable (%)	Migrated (#)	Migrated (%)	Delta (#)	Delta (%)
CQS1and2	19,220	5.23	19,118	5.21	-102	-0.53
CQS3	63,214	17.22	63,031	17.17	-183	-0.29
CQS4	72,744	19.81	72,711	19.8	-33	-0.05
CQS5	32,635	8.89	32,620	8.88	-15	-0.05
CQS6	65,042	17.71	65,008	17.71	-34	-0.05
CQS7	48,700	13.26	48,813	13.29	113	0.23
CQS8	65,617	17.87	65,871	17.94	254	0.39

Table D7 – 1-year change in ICAS PD

	Migrated (#)	Migrated (%)	Stable (#)	Stable (%)
PD	131,510	35.82	235,662	64.18

Robustness checks – Alternative hazard probability

We calculate all PDs, disaggregated by risk indicator, NACE sector, firm size, and region, using hazard probabilities associated with upper and lower bounds of the time range for each risk category and derived as the average between the upper and lower probabilities (Table 24).

Table D8 Annualised probability of occurrence of the HG events. Alternative hazard probability

Flood	Landslide
HPH: $T = [20; 50] \rightarrow p_u = 0.02 ; p_l = 0.05 \rightarrow \bar{p} = 0.035$	P4: $T = [1; 30] \rightarrow p_u = 0.033; p_l = 1 \rightarrow \bar{p} = 0.517$
MPH: $T = [100; 200] \rightarrow p_u = 0.005; p_l = 0.01 \rightarrow \bar{p} = 0.0075$	P3: $T = [30; 100] \rightarrow p_u = 0.01; p_l = 0.033 \rightarrow \bar{p} = 0.0217$
LPH: $T > 200 \rightarrow p_u = 0.002; p_l = 0.002 \rightarrow \bar{p} = 0.002$	P2: $T = [100; 300] \rightarrow p_u = 0.003; p_l = 0.01 \rightarrow \bar{p} = 0.0067$
	P1: $T > 300 \rightarrow \bar{p} = 0.0033$

Our results show that the average increase in PD exceeds 0.7 bp in the average scenario and is nearly three times higher in the upper-bound scenario. The most significant variations occur in the highest HG risk category, as well as in sectors and regions that were already among the most exposed in the baseline scenario (Table 12.25). Hence, the assumptions regarding return time are the most impactful. However, the baseline assumption – averaging the return time and converting it into a probability of occurrence – is the mainstream method for obtaining a combined return period (Raschke, 2021).

Table D9 One - year change in ICAS PD for different hazard probability

	Average PD increments (bp)			
	Baseline	Lower Bound	Average	Upper Bound
Panel A: Firms				
Total	1.0	0.6	1.7	2.8
Panel B: HG risk indicator				
0	0.0	0.0	0.0	0.1
Low	0.9	0.7	1.0	1.4
Medium	1.8	1.1	2.5	3.8
High	9.1	4.4	18.9	32.0
Panel C: NACE Sector				
Agriculture	1.9	1.2	5.2	8.7
Mining	1.0	0.6	3.7	6.9
Manufacturing	1.0	0.6	1.8	2.8
Electricity	0.7	0.3	1.4	2.8
Waste management	0.6	0.3	1.6	2.6
Construction	1.3	0.7	2.5	3.7

Trade	0.9	0.4	1.3	2.3
Hosting services	1.9	1.1	3.2	4.8
Transporting	1.3	0.7	2.3	4.0
ICT	0.8	0.4	0.9	1.4
Real Estate	0.6	0.4	0.8	1.3
Professional services	0.7	0.4	0.8	1.2
Administrative services	1.2	0.6	1.6	2.5
Education	1.0	0.7	1.2	1.8
Health services	1.1	0.6	1.7	2.6
Entertainment	0.8	0.5	1.6	2.4
Other services	1.1	0.7	1.6	2.5

Panel D: Size

Large	1.9	1.4	2.3	3.4
Medium	1.2	0.6	1.9	3.1
Small	1.1	0.6	1.9	3.0
Micro	0.9	0.5	1.7	2.7

Panel E: Region

Abruzzo	1.4	0.7	4.0	6.8
Aosta Valley	2.1	1.1	6.5	11.1
Apulia	0.5	0.2	1.3	2.3
Basilicata	0.8	0.4	1.8	3.0
Calabria	2.2	1.0	3.5	6.0
Campania	1.4	0.6	4.2	7.5
Emilia Romagna	1.6	1.1	2.1	3.1
Friuli Venezia Giulia	0.7	0.4	0.6	0.9
Lazio	1.3	0.6	2.1	3.6
Liguria	3.3	1.7	3.2	4.4
Lombardy	0.4	0.2	0.6	0.9
Marche	0.5	0.3	0.6	0.8
Molise	1.5	0.7	5.6	9.2
Piedmont	0.5	0.3	1.2	2.1
Sardinia	1.2	0.7	1.7	2.3
Sicily	1.0	0.4	1.9	3.2
Tuscany	1.8	0.2	0.4	0.6
Trentino-South Tyrol	0.5	1.3	2.6	3.9
Umbria	0.8	0.5	0.9	1.3

Robustness checks – Alternative flood vulnerability measure

To further corroborate our findings, we extend our analysis by considering two alternative measures of flood vulnerability. Specifically, we examine two scenarios: i) a mild scenario, in which PPE and WI lose 30 percent of their value; ii) an extreme scenario, in which PPE and WI lose up to 90 percent of their value. No significant differences arise with respect to the baseline, hence, assumptions about vulnerability are not crucial.

Table D10 One - year change in ICAS PD for different vulnerability level

	Average PD increments (bp)		
	Baseline	Mild	Extreme
Panel A: Firms			
Total	1.0	1.0	1.0
Panel B: HG risk indicator			
0	0.0	0.0	0.0
Low	0.9	0.9	1.0
Medium	1.8	1.8	1.9
High	9.1	8.9	9.3
Panel C: NACE Sector			
Agriculture	1.9	1.9	2.0
Mining	1.0	1.0	1.1
Manufacturing	1.0	1.0	1.0
Electricity	0.7	0.6	0.7
Waste management	0.6	0.6	0.6
Construction	1.3	1.2	1.3
Trade	0.9	0.8	0.9
Hosting services	1.9	1.9	1.9
Transporting	1.3	1.3	1.4
ICT	0.8	0.8	0.8
Real Estate	0.6	0.5	0.6
Professional services	0.7	0.7	0.7
Administrative services	1.2	1.2	1.2
Education	1.0	1.0	1.0
Health services	1.1	1.1	1.1
Entertainment	0.8	0.8	0.8
Other services	1.1	1.1	1.1
Panel D: Size			

Large	1.9	1.6	2.2
Medium	1.2	1.2	1.2
Small	1.1	1.1	1.1
Micro	0.9	0.9	1.0

Panel E: Region

Abruzzo	1.4	1.4	1.4
Aosta Valley	2.1	2.1	2.2
Apulia	0.5	0.5	0.5
Basilicata	0.8	0.8	0.8
Calabria	2.2	2.2	2.3
Campania	1.4	1.4	1.4
Emilia Romagna	1.6	1.6	1.7
Friuli Venezia Giulia	0.7	0.7	0.8
Lazio	1.3	1.2	1.3
Liguria	3.3	3.2	3.3
Lombardy	0.4	0.4	0.4
Marche	0.5	0.4	0.5
Molise	1.5	1.5	1.5
Piedmont	0.5	0.5	0.5
Sardinia	1.2	1.2	1.3
Sicily	1.0	1.0	1.1
Tuscany	1.8	0.4	0.5
Trentino-South Tyrol	0.5	1.7	1.8
Umbria	0.8	0.8	0.8
Veneto	0.8	0.8	0.8

Robustness checks – Single branch firms

To further corroborate our findings, we extend our analysis by considering firms with only one branch. No significant differences arise with respect to the baseline both in the overall exposure and in the PD increments. Therefore, the hierarchical methodology for assessing the importance of each local unit is robust.

Table D11 One - year change in ICAS PD for different vulnerability level

	Firms (#)	Firms (%)	Average PD increments (bp)
Panel A: Firms			
Total	221,201	32.4	1.0
Panel B: HG risk indicator - Max level			
0	145,242	67.6	0
Low	29,789	12.4	0.8
Medium	30,828	13.2	1.4
High	15,342	6.8	9.6

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