WORKING PAPER

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December 2025
2025/1129

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The Impact of Wildfires on Loss Given Default: Evidence from Defaulted Consumer Credits*

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December 16, 2025

Abstract

Research on natural disasters and credit risk mainly focuses on default probabilities. However, post-default outcomes remain largely unexplored, making the overall impact on credit losses unclear. We address this gap by providing novel empirical evidence on the impact of wildfires on credit losses through the loss given default channel. Exploiting the richness of a proprietary database on defaulted consumer credits in Italy, we determine granular wildfires exposures using satellite-based geospatial data on burned areas. We document a robust negative relationship between wildfire exposure during the post-default recovery period and realized recovery rates. This identifies a loss given default mechanism that complements existing evidence on default risk. The effect is heterogeneous: it is stronger when a larger share of agricultural land is burned and, consistent with evidence that natural disasters affect financially fragile households more severely, further amplified by local socioeconomic vulnerability. These findings call for integrating climate considerations into credit risk management beyond default risk.

Keywords: Natural disasters; Wildfires; Consumer credit; Credit risk; Loss given default
JEL codes: G21; G51; Q54

*We thank Itzhak Ben-David, Kris Boudt, Koen Inghelbrecht, Tong Li, Thaïs Nuvoli, Yasin Kürşat Önder, Rodolfo Raimondi, Luca Taschini, Jose Villegas, Raffaella Calabrese, and the participants of the Credit Scoring and Credit Control Conference XIX, the 30th Annual Conference of the European Association of Environmental and Resource Economists, the 8th EFiC Conference in Banking and Corporate Finance, the 3rd Conference on Sustainable Banking and Finance, and the IESEG and Ghent University Banking and Finance Seminars for their useful comments and suggestions. This work was supported by Research Foundation Flanders (FWO Vlaanderen) [grant numbers 11N7923N (Wolfgang Lefever) and 12A0S25N (Angelo Luisi)]. The views and opinions expressed in this paper are our own and do not necessarily reflect those of the National Bank of Belgium or the Eurosystem.

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1 Introduction

Climate change is increasing the frequency and severity of natural disasters (Bronstert, 2003; Bender et al., 2010; Turco et al., 2014; Bezner Kerr et al., 2022), and wildfires represent one of the most emblematic examples of this trend (Jolly et al., 2015; Cunningham et al., 2024). In the western United States, for instance, the period from 1984 to 2011 saw an average increase of seven large wildfires and 355 square kilometers of burned area per year (Dennison et al., 2014). In the European Union, 2017 and 2022 marked record levels of burned natural land (San-Miguel-Ayanz et al., 2018, 2023). Overall, climate change increased the global burned area by 15.8% between 2003 and 2019, and by 16.9% in the Mediterranean region (Burton et al., 2024).

The economic consequences of natural disasters are particularly pervasive. Direct damages include the destruction of property and productive assets and substantial physical and mental health costs, while indirect effects can arise through wider economic impacts, such as job losses and supply-chain breakdowns. Prior research shows that natural disasters have significant effects on both the real economy and the financial system, including reductions in output (Klomp and Valckx, 2014), employment (Deryugina, 2022), and local economic activity (Meier et al., 2023), as well as impacts on public finances and financial markets, such as higher government borrowing costs (Mallucci, 2022; Phan and Schwartzman, 2024), strained fiscal positions (Klomp, 2017), changes to firms' access to credit (Berg and Schrader, 2012; Koetter et al., 2020), and downward pressure on affected firms' stock and bond prices (Huynh and Xia, 2023). Wildfires, in particular, can generate substantial economic costs, including smoke-related labor earnings losses (Borgschulte et al., 2024), lower property values (Nicholls, 2019), higher medical expenditures (Johnston et al., 2021b), and losses in forestry and tourism (Rego et al., 2013; Johnston et al., 2021a). Recent evidence also shows that wildfire exposure worsens local fiscal conditions (Liao and Kousky, 2022; Jeon et al., 2024) and weakens firm performance (Tavor, 2024).

At the household level, natural disasters affect access to mortgage credit (Cortés and Strahan, 2017), labor supply (Groen et al., 2020), financial conditions and risk aversion (Johar et al., 2022), as well as consumer credit demand and indebtedness (Gallagher and Hartley, 2017; Del Valle et al., 2024). Although insurance payouts or public compensation can mitigate some of the negative impact on credit performance (Gallagher and Hartley, 2017; Gallagher et al., 2023; Biswas et al., 2023), the evidence consistently points to heightened financial fragility and a worsening of credit scores, ultimately resulting in higher delinquency and default rates (Ratcliffe et al., 2020; Kousky et al., 2020; Billings et al., 2022; Ho et al., 2023; Biswas et al., 2023; Contat et al., 2024; Calabrese et al., 2024).

Delinquency or default rates, however, capture only one component of credit losses. Credit risk models typically express expected losses as the product of three elements: (a) the probability of default (PD), (b) the loss given default (LGD), and (c) the exposure at default (EAD). Conditional on default, the EAD is already known to the creditor, making the key variable of interest the LGD—or, equivalently, the recovery rate (RR), since LGD = 1 - RR. The RR captures the portion of the unpaid debt that creditors manage to recover through collection efforts, legal processes, or asset liquidation.[1] Existing research on RR largely focuses on static credit-level characteristics such as borrower age, loan type, and recovery duration (see, for example, Nazemi et al., 2022), while also emphasizing the role of institutional and legal environments (Fedaseyeu, 2020) and time-varying macro-financial conditions (Distaso et al., 2025). Although a substantial literature examines the effects of natural disasters on PD, much less is known about their implications for post-default outcomes and recovery processes. This paper addresses this gap by empirically analyzing how wildfire exposure affects the recovery rate of defaulted consumer credits.

To study the effects of wildfires on credit risk via the LGD channel, we combine two unique datasets. The first is a proprietary dataset containing more than three million defaulted consumer credits in Italy, obtained from a third-party debt collection agency. The second is a geospatial dataset on burned areas derived from satellite imagery, allowing us to measure debtors' exposure to wildfires. By focusing on wildfires occurring during the recovery period, i.e., after credits have already defaulted and entered the debt collection process, we isolate the impact of wildfire exposure on recovery outcomes through loss given default. Our results reveal a robust negative relationship between wildfire exposure, both during and prior to the recovery period, and realized recovery rates. On average, credits in our sample that were exposed to wildfires during the recovery period saw a 2.7% decrease in the probability of successful recovery. The effect is stronger when wildfires affect more densely populated areas or regions with a higher share of agricultural land. Moreover, local socioeconomic conditions matter: individuals in vulnerable communities experience larger declines in recovery rates. By linking post-default recovery outcomes to wildfire exposure,

[1] The literature typically models the RR rather than the LGD (Bellotti and Crook, 2012).

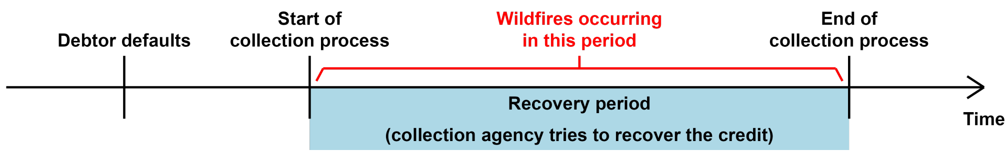
this study introduces a novel dimension to the intersection of climate risk and credit risk, advancing our understanding of both climate-related financial impacts and the determinants of credit losses.

Our paper is organized as follows. In Section 2, we outline the identification strategy employed to isolate the loss given default channel. Section 3 describes the datasets used in the analysis. Section 4 presents the empirical framework and results, and Section 5 concludes. There are three appendices. A explains the procedure for determining debtors' province of residence, B details the construction of variables used to analyze heterogeneous effects, and C contains robustness checks.

2 Identification strategy

To identify the effect of wildfire exposure on loss given default, we exploit the features of the third-party debt collection process. After a consumer defaults on their debt, the original creditor (e.g., a telecommunications service provider) transfers the defaulted credit to a third-party collection agency, which is authorized to pursue recoveries over a credit-specific maximum period stipulated in the contract, i.e., the *Recovery Period*. At the end of this period, collection rights go back to the original creditor, with outcomes of the recovery process ranging from no recovery to partial or full recovery. The debt collection process, which can only be initiated *after* the debtor has already defaulted, provides a convenient way to disentangle the factors that determine credit losses. While wildfires before and during the recovery period can both be reflected in recovery outcomes and affect credit losses, by definition, those occurring *during* the recovery period can only do so *conditional on default*. Hence, by focusing on these wildfires, we are able to isolate an impact through the loss given default channel. Figure 1 provides a visual representation of the timeline of the debt collection process. This structure is analogous to the handling of credit card defaults studied in Bellotti and Crook (2012), telecommunications-related debts managed by third-party collectors in Nazemi et al. (2022), and broader analyses of LGD determinants in Distaso et al. (2025).

Figure 1: Timeline of the debt collection process



The outcome of the debt collection process, i.e., the realized *Recovery Rate* of the defaulted consumer credit, represents the total of repayments made by the debtor to the collection agency during the recovery period, relative to the Total to Recover amount:

$$\mathrm{RR} = \frac{\text{Sum of repayments during recovery period}}{\text{Total to Recover}} \, . \tag{1}$$

We employ geospatial data on burned areas to determine the debtor's exposure to wildfires (BA), calculated as the ratio of burned area within the debtor's province of residence to the province's total area. We estimate the effect of wildfire exposure during the recovery period on the realized recovery rate while controlling for previous wildfire exposure, credit- and debtor-specific characteristics, as well as fixed effects capturing local conditions and time trends. By focusing on wildfires that occur during the recovery period, which cannot have caused the (already-defaulted) debtor to default, effects can only arise through a loss given default channel.

As an extension to the main analysis, we investigate whether the impact is moderated by the nature of the wildfires that the debtor was exposed to. Specifically, we examine the role of the proximity of the wildfires in the province to the debtor's own area of residence, as well as the population density and land cover type of the burned areas. Further, previous studies (Billings et al., 2022; Ratcliffe et al., 2020) suggest that the impact of natural disasters may be more severe for households in financially fragile conditions. Building on this, we examine whether the local socioeconomic environment of the debtor moderates the effect of wildfire exposure on recovery rates.

3 Data

3.1 Defaulted consumer credits

Data on defaulted consumer credits is sourced from a proprietary, anonymised database managed by a third-party collection agency in Italy. The database covers credits originating from the telecommunications and utilities sectors between 2013 and 2019. For each credit, we determine the realized recovery rate, the timing of the recovery period, and the debtor's province of residence.[2] Crucially, the latter two constitute the temporal and spatial dimensions necessary to determine the wildfire exposure of the debtor. Other observed features include the Total to Recover amount, the Principal share of the total (as opposed to interests and administrative fees levied by the original creditor), and an identifier for the original creditor. Finally, the database contains the last ten digits of the debtor's tax identification number (*codice fiscale*), enabling us to determine their sex and age at the start of the recovery process while preserving anonymity.

The credits in the database have a maximum recovery period of one year, in line with Bellotti and Crook (2012), Nazemi et al. (2022), and Distaso et al. (2025).[3] Consistent with prior evidence on recovery behavior in consumer credit portfolios (Thomas et al., 2012; Nazemi et al., 2022; Distaso et al., 2025), the recovery rates in the dataset follow a highly bimodal distribution, with 88% of credits being either fully recovered or not at all. As a binary outcome model is appropriate for the majority of observations, we exclude the subset of partially recovered credits with a continuous recovery rate.[4] Finally, we remove credits with a total to recover exceeding 10,000 EUR (less than 0.1% of observations) to ensure that the results are not skewed by outliers or measurement error.

The final sample comprises 3,482,037 defaulted consumer credits between 2013 and 2019. All 110 Italian provinces and 3,960 out of 3,970 postal codes are represented in the sample. The total amount to recover across all credits is almost 1.5 billion EUR. About 20% of credits, representing 9% of the total owed amount, were successfully recovered. The relatively large share of non-recovered credits is in line with the statistics for third-party collection reported by Thomas et al. (2012). Table 1 reports descriptive statistics for the characteristics of the defaulted credits. On average, the total amount to recover is roughly 425 EUR (median 250 EUR), with the principal making up over 90% of the total. The recovery period spans an average of four months and usually (for about 85% of credits)

[2]We match the postal code of the debtor, observed in the database, to Italian NUTS 3 regions (provinces). A provides a detailed explanation of the matching procedure.

[3]As the recovery period is measured in full months, credits with a recovery period shorter than one month cannot be assigned a wildfire exposure and are therefore excluded from the sample.

[4]In C.1, we discuss the continuous recovery rates in further detail and show that results are robust to including partially recovered credits.

does not extend beyond five months.

Table 1: Descriptive statistics for defaulted consumer credits

Variable	Mean	SD	P25	P50	P75	N
Total to Recover (EUR)	424.4	653.5	125.0	244.4	456.5	3,482,037
Principal (% Total)	91.7	15.1	89.1	98.6	100.0	3,482,037
Debtor Age	48.6	17.2	36.0	46.0	58.0	3,482,037
Recovery Period (months)	3.8	2.0	2.0	4.0	5.0	3,482,037

This table reports descriptive statistics for the defaulted consumer credits in the sample. *Total to Recover (EUR)* measures the total amount in EUR that the collection agency is authorized to collect from the debtor. It comprises the principal debt, interest, and administrative costs imposed by the original creditor, but not the handling fees charged by the collection agency. *Principal (% Total)* represents the percentage of the *Total to Recover (EUR)* that is principal debt, as opposed to interest and administrative costs. *Debtor Age* measures the age of the debtor at the start of the recovery period. *Recovery Period (months)* represents the length of the recovery period, during which the collection agency is authorized to pursue recoveries from the debtor, in full months.

3.2 Wildfire exposure

The variable of interest is debtors' wildfire exposure during the recovery period (BA_{RP}), which we define as the ratio of the total *burned area* in the debtor's province of residence during the recovery period to the province's total area. To construct this measure, we obtain high-resolution geospatial data on burned area perimeters in Europe from the European Forest Fire Information System (EFFIS) Burnt Areas database.[5] This database is constructed using semi-automatic analysis of MODIS and Sentinel-2 satellite imagery. First, fire-burned areas are mapped through an unsupervised procedure that uses a combination of band thresholds and ancillary information on land cover, active fire detection, and fire news. These initial delineations are then verified and corrected through visual inspection of the satellite images. Burn perimeters are updated twice a day and capture burned areas with a size of approximately 30 hectares or larger. The database covers about 95% of the total burned area in the EU.

First, we determine the burned area that occurred in each province in each month by

[5] `https://forest-fire.emergency.copernicus.eu/applications/data-and-services` (accessed in January 2025).

combining the EFFIS burned area data with geospatial data on Italian provinces provided by the Geographic Information System of the Commission (GISCO).[6] For wildfires that affect multiple provinces, we only count the intersecting area between the burn perimeter and each province. Then, using these province-month burned areas, we calculate debtors' exposure to wildfires during the recovery period, BA_{RP}, as the ratio of the total burned area in the debtor's province of residence during the recovery period to the province's total area. This variable only captures wildfires that occurred when the credit was in the hands of the collection agency, i.e., after the debtor had already defaulted with the original creditor. As the length of the recovery period is credit-specific, ranging from 1 to 12 full months, the number of months included in BA_{RP} also varies across credits. As we do not observe the exact starting date of the recovery period, we consider it to start in the month following the transfer of the defaulted credit to the collection agency. This is done to ensure that the measure does not capture any wildfires that occurred before the recovery process, a necessary condition for the isolation of a loss given default channel.[7] We also calculate debtors' wildfire exposure in the year preceding the recovery period, BA_{-1y}, to control for the effect of prior wildfires on the recovery rate.

Table 2 reports descriptive statistics for the wildfire exposure measures. As only a subset of credits in the sample was exposed to wildfires (21% for BA_{RP} and 44% for BA_{-1y}), we separately report statistics for these observations. Conditional on having any exposure, wildfires burned an average of 0.38% of the total province area during the recovery period and 0.53% in the year preceding the recovery period. The largest exposure observed in the sample (4.10%) was caused by the wildfires that affected the province of Naples in July and August 2017, which destroyed large portions of woodland surrounding the Vesuvius volcano.

[6] `https://ec.europa.eu/eurostat/web/nuts/overview` (accessed in January 2025). We use the 2016 version of the NUTS classification with 110 provinces. This corresponds to the provinces to which the debtor postal codes are matched.

[7] A potential concern is that this may lead BA_{RP} to include some days after the recovery period had already ended. Note, however, that the variable is constructed using a lower bound for the length of the recovery period as it is measured in full months, offsetting the shift in the end of the recovery period. In C.2, we provide a detailed discussion and show that the results are robust to excluding the last month from BA_{RP} altogether.

Table 2: Descriptive statistics for wildfire exposures

	Full sample			Observations with $BA > 0$					
Variable	Mean	SD	N	Mean	SD	P25	P50	P75	N
BA_{RP}	0.08	0.38	3,482,037	0.38	0.76	0.03	0.09	0.33	714,330
BA_{-1y}	0.23	0.64	3,482,037	0.53	0.88	0.04	0.19	0.52	1,526,120

This table reports descriptive statistics for the wildfire exposure variables. BA_{RP} and BA_{-1y} measure the burned area in the debtor's province of residence as a share of the total province area during the recovery period and the year preceding the recovery period, respectively. The left side of the table reports statistics for the full sample, including observations with no wildfire exposure. The right side of the table reports statistics for the observations with some wildfire exposure during the period in question (recovery period or preceding year).

3.3 Interaction variables

To investigate potential heterogeneities in the effect of wildfire exposure, we collect data on the nature of the wildfires that affected the debtor's province of residence and the local socioeconomic environment of the debtor. B provides a detailed description of the data collection and processing for the variables discussed in this section.

We determine the characteristics of wildfire exposures at a sub-province level by combining the EFFIS burned areas data with additional geospatial datasets. Separate measures are constructed for BA_{RP} and BA_{-1y} as they represent the characteristics of the specific burned areas captured by each variable. First, we calculate the share of the province-level burned area that occurred within the debtor's own postal code (*Postal Code Share*). Using additional geospatial data on Italian administrative units from the GISCO,[8] we divide burned areas in each province over its constituent postal codes and calculate each postal code's share in the total. Second, we determine the population density of wildfire-burned areas using high-resolution geospatial population data for Europe.[9] *Population Density* is expressed relative to the overall population density of the province, such that a value of 1 indicates that the burned areas have the same population density as the province in which they occurred. Third, we calculate the share of the burned area within each province that occurred on agricultural land (*Agricultural Land Share*). Wildfires can have impor-

[8] `https://ec.europa.eu/eurostat/web/nuts/local-administrative-units` (accessed in July 2025).

[9] `https://ec.europa.eu/eurostat/web/gisco/geodata/grids` (accessed in April 2025).

tant consequences for agriculture as they affect agricultural resources, labor, and products (Kabeshita et al., 2023). Hence, we investigate if a greater proportion of agricultural land in the burned areas, as opposed to mainly forests and other natural land, exacerbates the impact of wildfires. To do so, we collect land cover data at a 100-meter by 100-meter resolution from the Copernicus Land Monitoring Service and intersect each province-burned area intersection (polygon) with the 100 m^2 grid cells.[10] We then compute the share of the burned area that occurred in the 'Agricultural areas' land cover category and aggregate over all wildfires that occurred in the province. Panel A of Table 3 presents descriptive statistics for the variables capturing characteristics of the wildfire-burned areas.

To assess whether debtors residing in areas with higher socioeconomic vulnerability experience more adverse recovery outcomes due to wildfire exposure, we retrieve municipality data on unemployment and education from Italy's 2011 census,[11] as well as income data for the year 2011 (the most recent pre-sample year that is never included in BA_{-1y}) from the Italian Ministry of Economy and Finances (*Ministero dell'Economia e delle Finanze*).[12] We aggregate the municipality data to the level of postal codes to construct five variables capturing the local socioeconomic environment of the debtor: unemployment rate, youth unemployment rate, compulsory schooling non-attainment rate, taxable income per capita, and the share of taxpayers with income from self-employed labor. We express these postal code-level variables relative to the overall province value and subtract 1. Hence, a value of 0 indicates that the debtor lives in a postal code that is similar to the overall province in terms of the socioeconomic characteristic in question. Descriptive statistics for the measures capturing the debtor's local socioeconomic environment are presented in Panel B of Table 3.

[10] `https://land.copernicus.eu/en/products/corine-land-cover` (accessed in January 2025).

[11] `http://dati-censimentopopolazione.istat.it/Index.aspx` (accessed in July 2025).

[12] `https://www1.finanze.gov.it/finanze/analisi_stat/public/index.php?opendata=yes` (accessed in July 2025).

Table 3: Descriptive statistics for interaction variables

	Full sample			Observations with $BA > 0$					
Variable	Mean	SD	N	Mean	SD	P25	P50	P75	N
Panel A: Characteristics of wildfire-affected areas									
Postal Code Share$_{RP}$	0.01	0.08	3,482,037	0.05	0.16	0.00	0.00	0.00	713,677
Postal Code Share$_{-1y}$	0.02	0.10	3,482,037	0.05	0.15	0.00	0.00	0.02	1,525,772
Population Density$_{RP}$	0.04	0.18	3,482,037	0.20	0.34	0.00	0.08	0.25	712,406
Population Density$_{-1y}$	0.08	0.22	3,482,037	0.19	0.30	0.02	0.10	0.26	1,523,201
Agricultural Land Share$_{RP}$	0.04	0.13	3,482,037	0.20	0.23	0.01	0.13	0.33	714,330
Agricultural Land Share$_{-1y}$	0.09	0.17	3,482,037	0.21	0.21	0.04	0.15	0.34	1,526,120
Panel B: Local socioeconomic environment of debtor									
Unemployment Rate	0.01	0.16	3,473,810	0.01	0.16	-0.09	0.03	0.10	713,674
Youth Unemployment Rate	0.01	0.13	3,433,574	0.02	0.12	-0.03	0.03	0.09	707,514
Comp. Schooling Non-Att. Rate	-0.01	0.23	3,478,533	-0.01	0.24	-0.14	-0.01	0.10	713,294
Taxable Income Per Capita	0.02	0.16	3,482,037	0.03	0.18	-0.11	0.02	0.18	714,330
Share of Self-Employed Taxpayers	0.05	0.39	3,482,037	0.06	0.38	-0.24	0.05	0.33	714,330

This table reports descriptive statistics for the interaction variables used in the analysis of heterogeneous effects of wildfire exposure on recovery rates. Panel A describes the variables capturing characteristics of the wildfire-burned areas measured by BA_{RP} and BA_{-1y}. Separate variables are created for wildfire exposures during the recovery period (subscript RP) and wildfire exposures in the year preceding the recovery period (subscript *-1y*). The left side of the table reports statistics for the full sample, including observations with no wildfire exposure. The right side reports statistics for the observations with some wildfire exposure during the period in question (recovery period or preceding year). Panel B describes the variables capturing socioeconomic conditions of the debtor's postal code of residence. The values are divided by the province average and reduced by 1, such that they measure how much the debtor's local environment deviates from the overall province (in relative terms). The left side of the table reports statistics for the full sample, including observations with no wildfire exposure. The right side reports statistics for the observations with some wildfire exposure during the recovery period.

4 Results

We use a logistic regression model to estimate the effect of wildfire exposure on the probability of successfully recovering defaulted consumer credit i:

$$\text{logit}(\Pr(RR_i = 1)) = \beta_1 BA_{RP,i} + \beta_2 BA_{-1y,i} + CV_i'\delta + FE \,, \tag{2}$$

where $\text{logit}(p) = \ln(p/(1-p))$.

By excluding the subset of credits with a continuous recovery rate in the interval (0,1), the dependent variable RR_i is defined as an indicator for whether the credit was successfully recovered. The coefficient of interest, β_1, measures the effect of wildfire exposure during the recovery period on the recovery rate. As these wildfires occurred after the debtor had already defaulted, they cannot have caused the debtor to default. Given the recurrent nature of wildfires, we include BA_{-1y} to control for prior exposure, i.e., wildfires that occurred in the year preceding the recovery period.[13]

We include the following credit- and debtor-specific control variables (CV_i): (log) total to recover, principal (% of total), debtor age, and debtor sex. We also include several fixed effects (FE) to account for unobserved heterogeneity that could be related to both wildfire exposures and recovery rates. First, an identifier for the original creditor accounts for creditor-specific characteristics of the credits in the sample that are not captured by the variables in the database. Second, province fixed effects control for (time-invariant) differences in macroeconomic, social and financial conditions between provinces. As wildfires have an uneven spatial distribution across Italy, with southern regions experiencing larger and more frequent exposures, province fixed effects are crucial to avoid any correlation between wildfire exposure and local conditions spuriously driving the estimated effect on recovery rates. Third, we include year-month fixed effects, capturing the start of the recovery period, to account for common variation over time, such as macroeconomic shocks that affect the whole country, seasonality in recovery rates, etc. Finally, fixed effects for the length of the recovery period (in months) account for the fact that a longer recovery period is on average associated with higher wildfire exposure as more months are included in BA_{RP}.

4.1 The economic significance of wildfires

Table 4 reports the results of the baseline logistic regression in Columns (1) and (2), with standard errors clustered at the province level. The estimated coefficient on BA_{RP} is -0.118, negative and statistically significant at the 1% level. The corresponding odds ratio of 0.888 implies that a one-percentage-point increase in wildfire exposure during the recovery period reduces the odds of successful recovery by approximately 11.2%.

[13]The correlation between BA_{RP} and BA_{-1y} is 0.048, which is comparable in magnitude to the correlations among other regressors.

The baseline model includes BA_{-1y} to control for debtors' exposure to wildfires that occurred before the start of the recovery period. As a robustness check, we restrict the sample to debtors with no prior wildfire exposure. Columns (3) and (4) of Table 4 show the estimates for subsamples with at least one and two years without wildfire exposure preceding the recovery period, respectively. The results remain qualitatively unchanged, confirming a consistent negative association between wildfire exposure during the recovery period and the likelihood of successful recovery.

Table 4: Main results

	(1)	(2)	(3)	(4)
	Base model		No recent wildfires	
	Coefficient	Odds Ratio	1 year	2 years
BA_{RP}	-0.118***	0.888	-0.191**	-0.566**
	(-5.678)		(-2.434)	(-2.492)
BA_{-1y}	-0.058***	0.943		
	(-3.289)			
ln(Total to Recover)	-0.949***	0.387	-0.939***	-0.911***
	(-21.211)		(-21.375)	(-34.139)
Principal (% of Total)	0.029***	1.029	0.028***	0.029***
	(27.940)		(18.086)	(17.916)
Debtor Age	0.003***	1.003	0.004***	0.005***
	(8.692)		(9.249)	(10.179)
Fixed effects	Yes		Yes	Yes
Observations	3,482,037		1,955,917	1,503,473
Pseudo R^2	0.222		0.217	0.213

This table reports logistic regression results for the base model estimating the effect of wildfire exposure on recovery rates. Columns (1) and (2) report regression coefficients and associated odds ratios. Columns (3) and (4) report results for the subset of observations with no wildfire exposure for a period of at least one year and two years preceding the recovery period, respectively. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

To assess the economic significance of the estimated effects, we build a counterfactual in which none of the credits were exposed to wildfires during the recovery period (i.e., $BA_{RP} = 0$ for all observations). Comparing recovery rates predicted by the model under this scenario to the observed recovery rates allows us to evaluate how wildfires impacted the outcomes for the credits in the sample. We quantify the financial impact by comparing the actual recovered amounts in the sample to counterfactual recovered amounts under the alternative scenario, calculated as $\hat{RR} \times$ Total to Recover (EUR). We estimate that, on average, credits exposed to wildfires during the recovery period saw a 2.7% decrease in the probability of successful recovery as a result of this exposure. In financial terms, we quantify an overall loss of 3% in the total amount recovered from these wildfire-exposed credits, which in our sample amounts to roughly 700k EUR.

Importantly, a severe wildfire season can generate losses far exceeding the impacts discussed above. In 2017, for example, nearly two-thirds of credits with a recovery period covering June, July or August, were exposed to wildfires. Due to the intensity of the exposures, the probability of successful recovery decreased by on average 7.4%, resulting in an overall loss of 7.8% in the total amount recovered from exposed credits over this period.

We perform several robustness checks to assess the validity of the results. First, we include partially recovered credits in the estimation by (i) converting continuous recovery rates to zero or one in the binary outcome model, and (ii) using continuous recovery rates as dependent variable in an Ordinary Least Squares regression. Second, we exclude the last month of the recovery period from BA_{RP} to fully eliminate the possibility of capturing wildfires that occurred after the end of the recovery period. Third, we account for province-specific variation over time by (i) including socioeconomic control variables, such as per capita GDP, employment, and life quality, and (ii) including granular fixed effects interacting the debtor's province with different attributes of the recovery period (starting year, starting month, and length). Finally, as wildfire exposures are not distributed uniformly across space and time, we verify that the results are not driven by a particular province or year. To do so, we exclude each of the five provinces with the most wildfire-exposed credits, as well as each of the years in the sample period, in a separate regression. In each of the robustness checks, the estimated effects of wildfire exposure during both the recovery period and the preceding year remain negative and significant. An in-depth discussion and regression results are provided in C.

4.2 Heterogeneous effects of wildfire exposure

The baseline model estimates an unconditional effect of wildfire exposure, varying only with the size of the burned area, regardless of which areas in the province were burned or how vulnerable the debtor is to negative impacts. In reality, both of these factors could shape the way that wildfires affect recovery rates. First, the location and characteristics of wildfire-burned areas within the province might be relevant for several reasons. Wildfires in close proximity to the debtor's own place of residence may exacerbate negative effects as the likelihood of direct impacts for the debtor, such as material damages and health complications, increases. Similarly, a greater population density or agricultural land share of wildfire-burned areas could entail a larger impact on the population and economy of the province. Second, social and economic conditions of the debtor's local environment could influence the effect of wildfires. In addition to serving as a proxy for debtors' own vulnerability, local socioeconomic conditions may affect the efficiency of emergency response, resident assistance, and reconstruction efforts. In this section, we investigate potential heterogeneity in the impact of wildfires arising from these factors.

First, we examine heterogeneous effects relating to the location and characteristics of the wildfire-burned areas in the province. We interact the wildfire exposure variable, BA_{RP}, with measures capturing (1) the share of the total burned area in the province that occurred within the debtor's own postal code, (2) the population density of the areas burned during the recovery period relative to the overall population density of the province, and (3) the agricultural land share of the burned areas. We do the same for BA_{-1y} and measures capturing the characteristics of the areas burned in the previous year. The postal code share, population density, and agricultural land share variables are not included outside of the interaction terms, as they characterize the areas burned by wildfires and hence take on a meaningful value only when $BA > 0$. The interaction variables are demeaned using the average among observations with non-zero wildfire exposure, such that the coefficients on BA_{RP} and BA_{-1y} reflect the effects for an 'average' wildfire-exposed observation.

The regression results are presented in Table 5. Column (1) reports the results for the interaction between wildfire exposure and postal code share. The interaction is not significant, indicating that the effect of wildfires that occur within the debtor's own postal code is not significantly different from fires that occur in the wider province. Column (2) reports the results for population density. Both interaction term coefficients are negative and statistically significant, indicating that the adverse effect of wildfires on recovery rates is more pronounced when the wildfires affect more densely populated areas relative to the provincial average. More precisely, assuming that the population is uniformly distributed within each 1 km^2 population grid cell, the interaction between wildfire exposure and the relative population density of the burned areas represents the share of the total province population residing within the wildfire-affected areas. Hence, this result suggests that, for a given share of provincial land area burned, the negative impact of wildfires on recovery rates is stronger when a larger fraction of the province's population is directly exposed. Column (3) presents the results for the specification interacting wildfire exposure with the agricultural land share of the burned areas. Both interaction term coefficients are negative and statistically significant, indicating that the adverse impact of wildfires on recovery outcomes is more pronounced when a larger proportion of agricultural land is affected by the fires.

Table 5: Interactions with characteristics of wildfire-affected areas

	(1) Postal Code Share	(2) Population Density	(3) Agricultural Land Share
BA_{RP}	-0.122***	-0.134***	-0.132***
	(-5.700)	(-8.231)	(-7.868)
BA_{RP} × Wildfire $\text{Characteristic}_{RP}$	0.113	-0.177***	-0.161**
	(1.526)	(-2.783)	(-2.317)
BA_{-1y}	-0.060***	-0.069***	-0.073***
	(-3.377)	(-4.328)	(-5.125)
BA_{-1y} × Wildfire $\text{Characteristic}_{-1y}$	0.056	-0.132**	-0.147**
	(0.762)	(-2.072)	(-1.976)
ln(Total to Recover)	-0.949***	-0.949***	-0.949***
	(-21.212)	(-21.204)	(-21.209)
Principal (% of Total)	0.029***	0.029***	0.029***
	(27.938)	(27.963)	(27.950)
Debtor Age	0.003***	0.003***	0.003***
	(8.693)	(8.696)	(8.696)
Fixed effects	Yes	Yes	Yes
Observations	3,482,037	3,482,037	3,482,037
Pseudo R^2	0.222	0.222	0.222

This table reports logistic regression results for models interacting wildfire exposure with characteristics of the wildfire-burned areas. Column (1) includes interactions with the share of the total burned area in the province that occurred within the debtor's own postal code of residence. Column (2) includes interactions with the population density of the burned areas, relative to the average population density in the province. Column (3) includes interactions with the share of the burned areas that occurred on agricultural land. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Second, we turn to the debtor's local environment to examine whether socioeconomic conditions influence the effect of wildfire exposure on recovery outcomes. Specifically, we interact the wildfire exposure variable with five proxies for local socioeconomic conditions in the debtor's place of residence: the unemployment rate, the youth unemployment rate, the rate of non-attainment of compulsory schooling, average taxable income, and the share of taxpayers whose income derives (fully or in part) from self-employment. In contrast to the regressions reported in Table 5, these estimations include the level of the interaction variable, as it may independently affect the collection process and, more importantly, the level has a meaningful interpretation even in absence of wildfire exposure. As the interaction variables are centered on 0, representing the relative difference with the province average, the coefficients on BA_{RP} and BA_{-1y} represent the effects for a debtor who lives in a postal code that is similar to the overall province in terms of the socioeconomic characteristic in question.

The results in Table 6 indicate in Column (1) that the local unemployment rate does not significantly moderate the effect of wildfire exposure, although it does exhibit a significant negative direct effect on recovery rates. In Column (2), focusing on youth unemployment, we find that a higher youth unemployment rate relative to the provincial average amplifies the negative impact of wildfire exposure during the recovery period, while the youth unemployment rate itself remains negatively associated with recovery. Column (3) shows that debtors living in postal codes with a higher compulsory-schooling non-attainment rate (i.e., lower educational attainment) experience a more pronounced negative impact from wildfire exposure during the recovery period. Column (4) reports that postal codes with higher average taxable income (relative to the provincial mean) have, on average, a lower likelihood of recovery; however, this variable does not significantly alter the effect of wildfire exposure. Finally, Column (5) examines the share of taxpayers whose income derives from self-employment. Postal codes with a larger share of self-employed income earners tend to have lower recovery rates on average, and, importantly, a higher self-employment share is associated with a stronger negative effect of wildfire exposure. Although this effect is statistically significant only at the 10 percent level, it nevertheless suggests that areas characterized by more volatile or less stable sources of income may be particularly susceptible to the economic disruptions induced by wildfires.

Table 6: Interactions with variables capturing debtor's local socioeconomic environment

	(1) Unemployment Rate	(2) Youth Unemployment Rate	(3) Compulsory Schooling Non-Att.	(4) Taxable Income (avg. p.p.)	(5) Share of Taxpayers with Self-Employed Labor Income
BA_{RP}	-0.117***	-0.115***	-0.117***	-0.118***	-0.119***
	(-5.451)	(-5.351)	(-5.495)	(-5.847)	(-5.890)
BA_{RP} × SocioEcon	-0.048	-0.150**	-0.089**	-0.075	-0.047*
	(-0.703)	(-1.977)	(-2.373)	(-1.095)	(-1.887)
BA_{-1y}	-0.059***	-0.058***	-0.058***	-0.058***	-0.059***
	(-3.302)	(-3.218)	(-3.191)	(-3.465)	(-3.451)
BA_{-1y} × SocioEcon	0.063	-0.005	-0.060	-0.049	-0.025
	(1.203)	(-0.113)	(-1.318)	(-0.641)	(-0.797)
SocioEcon	-0.435***	-0.526***	0.002	-0.334***	-0.165***
	(-5.971)	(-6.871)	(0.042)	(-3.788)	(-6.647)
ln(Total to Recover)	-0.949***	-0.950***	-0.949***	-0.949***	-0.949***
	(-21.150)	(-20.927)	(-21.212)	(-21.204)	(-21.199)
Principal (% of Total)	0.029***	0.029***	0.029***	0.029***	0.029***
	(27.678)	(27.438)	(27.958)	(28.066)	(28.061)
Debtor Age	0.003***	0.003***	0.003***	0.003***	0.004***
	(8.450)	(8.610)	(8.570)	(8.639)	(8.691)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,473,803	3,433,570	3,478,533	3,482,037	3,482,037
Pseudo R^2	0.223	0.223	0.222	0.222	0.223

This table reports logistic regression results for models interacting wildfire exposure with socioeconomic characteristics of the debtor's postal code of residence, relative to the province average. Columns (1) to (5) include interactions with: (1) unemployment rate, (2) youth unemployment rate, (3) compulsory schooling non-attainment rate, (4) average taxable income per person, (5) share of taxpayers with (some) self-employed labor income. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

5 Conclusion

This paper provides the first empirical evidence that wildfires increase loss given default in the consumer credit industry. Drawing on a large dataset of defaulted consumer credits from the telecommunications and utilities sectors, combined with geospatial data on burned areas, we find a robust negative relationship between debtors' exposure to wildfires and realized recovery rates. By focusing on wildfires that occur during the recovery period of already-defaulted consumer credits, while controlling for prior wildfire exposure, we isolate a loss given default channel through which wildfires affect credit losses. A one-percentage-point increase in exposure reduces the odds of successful recovery by approximately 11.2 percent. The magnitude of this effect depends on the characteristics of the burned areas and the local socioeconomic environment of the debtor. Wildfires in more densely populated areas or those affecting larger shares of agricultural land lead to a larger decline in recovery rates. Consistent with existing evidence that natural disasters have a stronger impact on financially vulnerable households, our results indicate that local socioeconomic fragility may amplify the negative effect of wildfire exposure on debt recovery.

Overall, our findings demonstrate that wildfires can increase credit losses by raising loss given default, even when default probabilities are unaffected. While these effects already have a material financial impact in the historical data, the changes to wildfire regimes brought about by climate change –longer fire seasons, expansion of at-risk areas, and greater wildfire intensity– are likely to amplify these losses. In this context, our results highlight the need for credit risk management to integrate physical climate risks in a comprehensive manner that extends beyond the probability of default.

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A Matching Italian postal codes to provinces

The defaulted consumer credits database contains the debtor's postal code of residence, which we use to determine the debtor's province. In a first step, we clean the raw postal codes. As all Italian postal codes consist of five digits, codes containing non-numeric characters are removed from the sample. We also drop codes with fewer than three or more than five digits, and add leading zeroes to those with three or four digits. Next, we link the remaining postal codes –all five-digit numbers– to the province in which they are located using a matching table.[14] This table contains the postal code and province of all Italian municipalities that existed in the year 2011. In total, 8,092 municipalities are linked to 3,970 postal codes across 110 provinces. As postal codes are subject to occasional change, the matching table does not cover all postal codes observed in our sample period 2013-2019. To solve this, we manually assign unmatched postal codes to the corresponding 2011 postal code using online resources. By performing this procedure for all postal codes that represent at least 1% of unmatched observations, we successfully match 56% of unmatched observations. While the majority of postal codes lie within a single province, ten postal codes cross province boundaries. Observations associated with these postal codes are removed from the sample as a unique province, and hence wildfire exposure, cannot be determined.

Usually, Italian municipalities are associated with a single postal code, while postal codes are a combination of one or more municipalities. This many-to-one relationship between municipalities and postal codes enables us to aggregate socioeconomic data, available at the level of municipalities, to the level of the postal codes observed in the credits dataset. However, 41 municipalities (mostly cities) have multiple postal codes within their territory. All postal codes belonging to the same municipality start with the same three to four digits. Hence, we aggregate these to form a single postal code 'group' for the municipality, ensuring a many-to-one relationship between all municipalities and postal codes. For instance, all postal codes in the municipality of Rome follow the pattern '001XX', with the last two digits representing the specific area or neighborhood within Rome. We treat all postal codes starting with '001' as a single postal code covering the entire municipality of Rome.

B Construction of interaction variables

B.1 Postal code share of burned areas

To calculate the share of the province-level burned area that occurred within the debtor's own postal code (*Postal Code Share*), we first calculate burned areas by municipality before aggregating to the level of postal codes. We obtain geospatial data for the 2011 Italian municipalities from the Local Administrative Units (LAU) classification of the GISCO.[15] We intersect this data with the EFFIS burned area outlines to calculate the monthly burned

[14] `https://lab.comuni-italiani.it/download/comuni.html` (accessed in July 2025).

[15] `https://ec.europa.eu/eurostat/web/nuts/local-administrative-units` (accessed in July 2025).

area (in km^2) for each municipality. Next, we aggregate to the level of postal codes by summing the burned areas of all municipalities belonging to the same postal code. This step utilizes a matching table that links Italian municipalities and postal codes for the year 2011.[16] Finally, for each credit, we determine the burned area in the debtor's postal code of residence during the recovery period and express this as a share of the total burned area in the province over the same period ($\textit{Postal Code Share}_{RP}$). We do the same thing for the burned areas in the year preceding the recovery period ($\textit{Postal Code Share}_{-1y}$).

B.2 Population density of burned areas

We calculate the population density of burned areas within each province relative to the average population density of the province. To do so, we collect geospatial population data for Europe on a 1-km by 1-km grid from the GISCO, available for the years 2006, 2011, 2018 and 2021.[17] We use the 2011 version of the data as this is the latest available year before the start of our sample period (2013-2019). Additionally, this year aligns with the timing of the census data used in the analysis of the local socioeconomic environment of the debtor, as well as the table used to match debtors' postal codes to provinces.

We intersect the EFFIS burned area polygons with the 1 km^2 population grid cells. Grid cells covering multiple provinces are first split along province boundaries. This allows us to determine the share of each population grid cell within a province that was burned by a given wildfire, and hence the overall population density of the area burned by that wildfire in the province. We then calculate the average population density of the burned areas across all wildfires that affected the debtor's province of residence during the recovery period ($\textit{Population Density}_{RP}$) and the year preceding the recovery period ($\textit{Population Density}_{-1y}$). We express these measures relative to the overall population density of the province, such that a value of 1 indicates that the population density of the wildfire-burned areas is equal to the population density of the province.

B.3 Agricultural land share of burned areas

To calculate the share of the total burned area within each province that occurred on agricultural land, we obtain CORINE Land Cover (CLC) data from the Copernicus Land

[16] `https://lab.comuni-italiani.it/download/comuni.html` (accessed in July 2025).

[17] `https://ec.europa.eu/eurostat/web/gisco/geodata/grids` (accessed in April 2025).

Monitoring Service.[18] The CLC database, established to standardize land cover data collection across Europe, classifies land cover into 44 categories at a 100-meter by 100-meter resolution. It is primarily derived from ortho-corrected high-resolution satellite imagery, supplemented by topographic maps, ortho-photos, and ground survey data (Copernicus Land Monitoring Service, 2021). The database is updated every six years. For our analysis, we collect the raster files for the years 2006, 2012, and 2018.

We intersect the EFFIS burned areas polygons, split along province boundaries if more than one province was affected, with the 100 m^2 land cover grid cells. As such, we split each wildfire that affected a given province along the land cover grid cells to determine the exact land cover composition of the burned area. For each province, we calculate the monthly burned area (in km^2) that occurred in the 'Agricultural areas' land cover category. This category includes the following subcategories: (i) arable land, (ii) permanent crops, (iii) pastures, and (iv) heterogeneous agricultural areas.[19] Finally, for each credit, we calculate the agricultural land share of burned areas across all wildfires that affected the debtor's province of residence during the recovery period ($Agricultural\ Land\ Share_{RP}$) and the preceding year ($Agricultural\ Land\ Share_{-1y}$).

For each burned area, we determine the land cover distribution using the most recent version of the CLC database that could not have been affected by the occurrence of that wildfire. We use the 2006 version of the CLC database for wildfires that occurred before 2013 (which can be included in BA_{-1y}), the 2012 version for wildfires that occurred between 2013 and 2018, and the 2018 version for wildfires that occurred from 2019 onwards.

B.4 Local socioeconomic environment of the debtor

To capture the local socioeconomic environment of the debtor's area of residence, we collect municipality-level data from two administrative data sources. We obtain data on resident population, unemployment rate, youth unemployment rate, and compulsory schooling non-attainment rate from the 2011 census, made available by the Italian National Institute of Statistics (Istat).[20] We also obtain data on the number of taxpayers, total taxable

[18] `https://land.copernicus.eu/en/products/corine-land-cover` (accessed in January 2025).

[19] For an overview of the 44 CLC land cover categories, see `https://land.copernicus.eu/en/technical-library/clc-illustrated-nomenclature-guidelines/@@download/file` (accessed in January 2025).

[20] `http://dati-censimentopopolazione.istat.it/Index.aspx` (accessed in July 2025).

income (in EUR), and the number of taxpayers with income from self-employment for the year 2011 from the Italian Ministry of Economy and Finances (*Ministero dell'Economia e delle Finanze*).[21] The motivation for using time-invariant data for the year 2011 is threefold. First, before 2018, the population census was conducted once every ten years. Hence, for most observations, the 2011 census constitutes the latest available data that predates the measurement of wildfire exposure during the recovery period. While the next available census dataset, representing the year 2018, predates the recovery period of credits in 2019 (i.e., the final year of the sample), wildfires that occurred in 2018 are captured by BA_{-1}. Second, the permanent (annual) census of population and housing introduced in 2018 differs from the ten-yearly censuses that preceded it. The new methodology no longer involves a survey of all Italian households, instead combining a representative sample across 2,800 municipalities with administrative data. This change makes comparison with the 2011 census results difficult. Third, municipalities occasionally undergo boundary changes or disappear completely as a result of fusions with other municipalities. This results in yearly changes in the composition of municipality-level datasets. Given that we observe the municipality-postal code linkages for the year 2011, we can aggregate 2011 municipality data to the level of postal codes without losing observations due to territorial changes.

We aggregate the census data, measuring municipality-level unemployment and education rates, to the level of postal codes using a population-weighted average across all municipalities that belong to the same postal code. For the income data, we first sum the variables to calculate the total number of taxpayers, taxable income (in EUR), and number of self-employed taxpayers in each postal code. Then, we calculate for each postal code the average taxable income per taxpayer and the share of taxpayers whose income stems (entirely or partly) from self-employment. As we aim to analyze whether wildfires within a given province affect recovery rates differently depending on the *local* socioeconomic environment of the debtor, we express these variables relative to the overall average for the province in which each postal code is located. To determine the province values, we use the same steps as used for the postal codes. The final variables used in the analysis measure the relative difference of the debtor's postal code of residence with the overall value in the province. For instance, a value of 0.05 for the unemployment rate variable indicates that

[21] `https://www1.finanze.gov.it/finanze/analisi_stat/public/index.php?opendata=yes` (accessed in July 2025).

the debtor lives in a postal code with an unemployment rate that is 5% higher than the overall unemployment rate in the province.

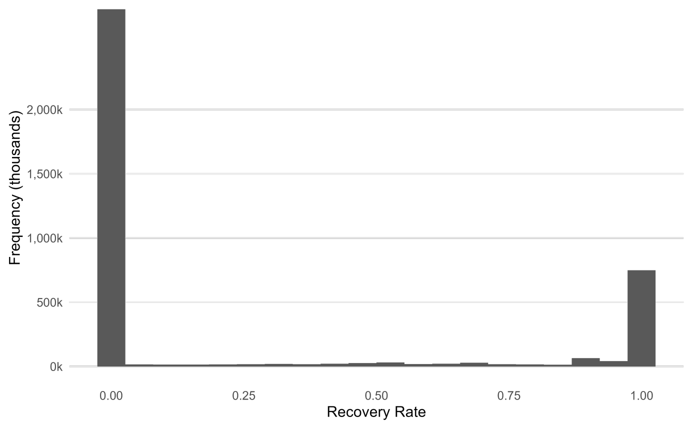
For the variables derived from the census data, we set a postal code's value to missing if any of the constituent municipalities have a missing value. While all variables have good coverage, this introduces slight variation in the sample size of the regressions. The income dataset deliberately censors the exact number of individuals with income stemming from self-employment for municipalities in which the value is smaller than four, resulting in 411 municipalities (out of a total of 8,092) with a missing value. To resolve this, we fill censored values by allocating 'excess' self-employed individuals in each region to the censored municipalities. First, we obtain the true number of self-employed individuals in each region from the corresponding region-level income data, also obtained from the Italian Ministry of Economy and Finances. Next, we sum the number of self-employed individuals across all municipalities with an observed value that belong to the same region. The difference between these two represents the 'excess' self-employed individuals in each region that are not accounted for in the municipality data. We allocate these individuals across the municipalities with a censored value in proportion to their resident population and round down to the nearest whole number.

C Robustness checks

C.1 Include credits with continuous recovery rate

As shown in Figure 2, the recovery rates in the dataset follow a highly bimodal distribution, with 88% of credits having a recovery rate of exactly 0 or 1. This means that, in most cases, the collection agency either manages to recover the full amount or nothing at all. This pattern is consistent with prior evidence on recovery behavior in consumer credit portfolios (Thomas et al., 2012; Nazemi et al., 2022; Distaso et al., 2025). In the main analysis, we exclude the credits with a continuous recovery rate in the $(0, 1)$ interval from the sample and define the dependent variable as an indicator for whether the credit was successfully (and fully) recovered. This is motivated by the fact that the third-party debt collection process usually does result in either full or no recovery, making a binary outcome model the appropriate modeling choice for the majority of observations.

Figure 2: Distribution of recovery rate



As a robustness check, we include partially recovered credits in the logistic regression model by assigning them a binary outcome (recovered or unrecovered) based on recovery rate thresholds. Columns (1) to (3) in Table 7 report the results for specifications in which a credit is considered to be successfully recovered (and unrecovered otherwise) using the following thresholds for the recovery rate: (1) $RR = 1$, (2) $RR \geq 0.50$, and (3) $RR > 0$. Compared to the baseline model, results remain qualitatively unchanged under these alternative specifications.

Table 7: Include partially recovered credits by converting recovery rates to binary

	(1) $RR = 1$	(2) $RR \geq 0.50$	(3) $RR > 0$
BA_{RP}	-0.109***	-0.087***	-0.079***
	(-5.474)	(-5.663)	(-5.612)
BA_{-1y}	-0.053***	-0.046***	-0.039***
	(-3.209)	(-3.124)	(-2.836)
ln(Total to Recover)	-0.956***	-0.785***	-0.584***
	(-22.175)	(-24.956)	(-23.197)
Principal (% of Total)	0.030***	0.024***	0.016***
	(31.036)	(27.945)	(20.447)
Debtor Age	0.003***	0.004***	0.005***
	(7.650)	(10.275)	(11.981)
Fixed effects	Yes	Yes	Yes
Observations	3,946,366	3,946,416	3,946,416
Pseudo R^2	0.208	0.159	0.134

This table reports logistic regression results for the base model using an extended sample that includes partially recovered credits. Continuous recovery rates (i.e., $RR \in (0,1)$) are converted to 0 or 1 based on a threshold value. The dependent variable is thus an indicator for successful recovery. Columns (1) to (3) consider a credit successfully recovered if the recovery rate is (1) equal to 1, (2) greater than or equal to 0.50, and (3) greater than zero, such that the dependent variable indicates whether any amount was recovered. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Some loss given default modeling frameworks employ a two-stage procedure: a classification step distinguishing fully recovered and unrecovered cases, followed by a regression step modeling partial recoveries for credits with recovery rates in the $(0, 1)$ interval (Bellotti and Crook, 2012). In our dataset, however, only about 12% of credits fall within this intermediate range and, of these, only 17% were exposed to wildfires during the recovery period. The limited sample size and variation in wildfire exposure render a second-stage regression statistically fragile and potentially driven by noise rather than signal. However, as a robustness check, we confirm that the negative effect of wildfire exposure on recovery rates is also present and statistically significant for the subset of partially recovered credits. Column (1) of Table 8 reports the results for a regression modeling the (continuous) recovery rates of partially recovered credits using Ordinary Least Squares (OLS). Despite the limited sample size, the negative effect of BA_{RP} remains highly significant. For completeness, Columns (2) and (3) report the OLS results for the credits with a binary recovery rate (i.e., the sample used in the main analysis) and a sample including all credits, respectively.

Table 8: Include partially recovered credits in OLS regressions

	(1) Partially recovered credits	(2) Credits with binary RR	(3) Full sample
BA_{RP}	-0.003***	-0.012***	-0.011***
	(-2.626)	(-6.605)	(-6.181)
BA_{-1y}	-0.002*	-0.006**	-0.005**
	(-1.889)	(-2.411)	(-2.131)
ln(Total to Recover)	-0.117***	-0.113***	-0.117***
	(-77.996)	(-48.882)	(-52.189)
Principal (% of Total)	0.002***	0.003***	0.003***
	(25.321)	(18.117)	(20.374)
Debtor Age	0.000	0.001***	0.001***
	(-1.609)	(10.266)	(11.119)
Fixed effects	Yes	Yes	Yes
Observations	464,331	3,482,086	3,946,417
Adjusted R^2	0.235	0.213	0.185

This table reports results for Ordinary Least Squares (OLS) regressions. Column (1) uses partially recovered credits, which are excluded from the main analysis, as the estimation sample. The dependent variable is the credits' continuous recovery rate. Column (2) uses credits with a binary recovery rate, as in the main analysis. Column (3) includes all credits, combining continuous and binary recovery rates. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

C.2 Timing of recovery period

The main variable of interest, BA_{RP}, measures the total burned area in the debtor's province of residence during the recovery period, expressed as a share of the total province area. For the construction of this variable, the recovery period is assumed to begin on the first day of the month following the transfer of the defaulted credit to the collection agency, and conclude at the end of the last month that is fully included in the recovery period. This approach ensures that BA_{RP} does not include any wildfires that occurred before the start of the recovery period, of which we cannot be certain that they occurred after the debtor had already defaulted on their debt with the original creditor. Instead, the month of the credit's transfer to the collection agency is the last month included in BA_{-1y}, the variable capturing the debtor's exposure to wildfires in the year preceding the recovery period.

To illustrate, consider the following example. A defaulted consumer credit is transferred to the collection agency on 26 July 2015 and has a recovery period of 130 days. To determine the debtor's wildfire exposure, we consider the recovery period to begin on 1 August 2015 and last for 4 full months. Hence, BA_{RP} captures all wildfires that occur in the debtor's province of residence between August and November 2015.

A potential concern is that shifting the start of the recovery period to the first day of the month following the transfer of the credit to the collection agency also shifts the end date of the recovery period backward. This can occasionally lead BA_{RP} to include some wildfires that occurred in the days after the recovery period had already ended and therefore cannot possibly affect the recovery rate. Two arguments alleviate this concern. First, by measuring the length of the recovery period in full months, we use a lower bound of the true period length, offsetting the backward shift in the end date of the recovery period. Second, as a robustness check, we adopt a more conservative definition of wildfire exposure during the recovery period, BA_{RP-1m}, which excludes the last month of the recovery period entirely. This definition eliminates any possibility of including days outside of the recovery period. Note that this shortens the recovery period of each credit by a full month for the measurement of wildfire exposure, limiting the sample to credits with a recovery period of at least two months. The results of the specification using BA_{RP-1m} are reported in Table 9. The estimated effects of wildfire exposure are very similar to the baseline model, confirming that our results do not depend on the exact end date of the recovery period.

Table 9: Exclude last month of recovery period from wildfire exposure variable (BA_{RP})

	(1)
BA_{RP-1m}	-0.122***
	(-6.089)
BA_{-1y}	-0.058***
	(-3.184)
ln(Total to Recover)	-0.977***
	(-23.132)
Principal (% of Total)	0.028***
	(27.831)
Debtor Age	0.003***
	(8.166)
Fixed effects	Yes
Observations	3,209,395
Pseudo R^2	0.205

This table reports the results for an estimation using a more conservative measure of wildfire exposure, BA_{RP-1m}, which excludes the last month of the recovery period. Credits with a recovery period of one month are excluded from the sample as they cannot be assigned a wildfire exposure using this alternative measure. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

C.3 Control for province-specific time variation

The main analysis includes province fixed effects to account for unobserved, time-invariant heterogeneity between provinces. In this section, we verify that the results are not driven by province-specific variation that may be correlated with wildfire occurrence using two different approaches to control for time-varying province characteristics.

First, we control for socioeconomic conditions in the province using control variables. We obtain yearly data for Italian provinces (NUTS 3 regions) from Eurostat: per capita Gross Domestic Product (GDP), number of employed persons, population, as well as the number of assaults and the number of homicides per 1,000 inhabitants. Additionally, we retrieve province life quality scores created by Il Sole 24 Ore as a broad measure of inhabitants' living conditions that covers various aspects of life quality.[22] We include the following control variables in the regression: natural log of per capita GDP, employed persons rate (calculated as the number of employed persons divided by the province population), assault rate, homicide rate, and the life quality score. For each variable, we include both the value for the calendar year of the start of the recovery period and the previous year. The results, reported in Column (1) of Table 10, are very similar to the results of the baseline model.

Second, we include granular fixed effects that interact the province dummies with time dummies to filter out all province-specific variation along a given time dimension. In three separate specifications, we interact the debtor's province of residence with the starting year, the starting month-of-year, and the length (in months) of the recovery period. Together, these elements determine the timing of the recovery period and hence the wildfire exposure within a given province. The regression results, reported in Table 10, show that the estimated effects are highly significant and similar in magnitude to the baseline results. Column (2) includes province-year dummies, filtering out any province-specific variation over time that could affect recovery rates. Hence, the coefficient for BA_{RP} is only driven by variation in wildfire exposure stemming from differences in the starting month and the length of the recovery period for credits acquired by the collection agency in the same province-year. Column (3), including province-month of year dummies, accounts for potential province-specific seasonality in both recovery rates and wildfire occurrence. Identification for the effect of BA_{RP} relies on variation in wildfire exposure across years and recovery period lengths between credits acquired in the same province-month of year. Finally, we consider the length of the recovery period of the defaulted consumer credits. The length of the recovery period agreed upon between the collection agency and the original creditor may be influenced by the parties' expectations regarding the chances of successful recovery of the credit. As BA_{RP} is a sum of all wildfires that occurred during the recovery period, this measure has a positive correlation with the number of months in the recovery period by construction. While the baseline model already accounts for potential spurious correlation between wildfire exposure and recovery rates through the length of the recovery period across the full sample, we verify that any remaining between-province differences are not

[22] `https://lab24.ilsole24ore.com/qualita-della-vita/` (accessed in January 2025).

driving the main results. Column (4) reports the results for a specification including dummies that interact the debtor's province of residence with the length of the recovery period (in months). These results are only driven by variation in the starting year-month of the recovery period of credits from the same province with the same recovery period length.

Table 10: Control for province-specific time variation

	(1)	(2)	(3)	(4)
		Fixed Effect: Province ×		
	Macro & Social	Year	Month of Year	RP (no. months)
BA_{RP}	-0.126***	-0.113***	-0.139***	-0.116***
	(-7.083)	(-6.999)	(-4.016)	(-5.749)
BA_{-1y}	-0.056***	-0.047**	-0.055***	-0.047***
	(-3.469)	(-2.534)	(-3.317)	(-3.025)
ln(Total to Recover)	-0.957***	-0.951***	-0.949***	-0.944***
	(-20.931)	(-21.549)	(-21.238)	(-21.096)
Principal (% of Total)	0.029***	0.029***	0.029***	0.029***
	(27.581)	(29.635)	(29.694)	(29.536)
Debtor Age	0.003***	0.004***	0.004***	0.003***
	(8.676)	(9.376)	(9.793)	(9.242)
Macro and Social Controls	Yes	No	No	No
Fixed effects	Yes	Yes	Yes	Yes
Province-Year	No	Yes	No	No
Province-Month of Year	No	No	Yes	No
Province-RP (no. months)	No	No	No	Yes
Observations	3,405,625	3,482,037	3,482,037	3,481,316
Pseudo R^2	0.224	0.225	0.226	0.225

This table reports logistic regression results for specifications that account for province-specific time variation. Column (1) includes province-level macroeconomic and social control variables: natural log of per capita GDP, employed persons rate, assault rate, homicide rate, and life quality score. For each of the variables, both a contemporaneous measure and a one-year lag are included. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Columns (2) to (4) account for province-time variation by interacting the province fixed effect with an attribute of the recovery period: (2) starting year, (3) starting month of year, and (4) length (no. months). Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

C.4 Leave-one-out analysis

To confirm that the results are not driven by a particular province or year, we re-estimate the model, each time leaving out all credits from a specific province or year. First, we exclude the five provinces with the most wildfire-exposed credits in the sample. Columns (1) to (5) of Table 11 report the regression results for estimations excluding all credits originating from (1) Naples, (2) Palermo, (3) Rome, (4) Caserta, and (5) Catania. Despite these provinces making up a considerable share of the sample, the estimated effects remain highly significant and similar in magnitude.

Table 11: Exclude provinces with highest number of wildfire-exposed credits

	(1) Naples	(2) Palermo	(3) Rome	(4) Caserta	(5) Catania
BA_{RP}	-0.163***	-0.118***	-0.109***	-0.115***	-0.116***
	(-6.638)	(-5.758)	(-6.345)	(-5.884)	(-6.179)
BA_{-1y}	-0.087***	-0.062***	-0.051***	-0.051***	-0.058***
	(-3.440)	(-3.164)	(-3.274)	(-3.831)	(-3.430)
ln(Total to Recover)	-0.919***	-0.940***	-0.976***	-0.969***	-0.946***
	(-25.958)	(-21.025)	(-22.959)	(-22.478)	(-20.652)
Principal (% of Total)	0.029***	0.029***	0.030***	0.029***	0.029***
	(27.161)	(27.658)	(29.570)	(27.331)	(27.542)
Debtor Age	0.003***	0.003***	0.003***	0.004***	0.003***
	(7.946)	(8.626)	(7.718)	(9.644)	(8.543)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,096,639	3,360,426	3,119,629	3,355,819	3,370,916
Pseudo R^2	0.214	0.221	0.223	0.220	0.221

This table reports logistic regression results for specifications that exclude a different province in each column. From left to right, the following provinces are excluded from the estimation: (1) Naples, (2) Palermo, (3) Rome, (4) Caserta, and (5) Catania. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Second, we leave out each of the seven years in the sample period (2013 to 2019) from the estimation. Results are reported in Columns (1) to (7) of Table 12. Again, results remain significant and negative. The biggest change is observed when excluding all credits whose recovery period started in the year 2017, a year in which Italy experienced particularly severe wildfires.

Table 12: Exclude each year of the sample period

	(1) 2013	(2) 2014	(3) 2015	(4) 2016	(5) 2017	(6) 2018	(7) 2019
BA_{RP}	-0.109***	-0.111***	-0.103***	-0.126***	-0.087*	-0.130***	-0.123***
	(-5.412)	(-5.603)	(-5.362)	(-5.240)	(-1.888)	(-5.162)	(-6.375)
BA_{-1y}	-0.064**	-0.056***	-0.045***	-0.064***	-0.064***	-0.056***	-0.059***
	(-2.558)	(-3.226)	(-2.891)	(-3.645)	(-3.701)	(-2.702)	(-4.020)
ln(Total to Recover)	-0.941***	-0.939***	-0.961***	-0.951***	-0.938***	-0.955***	-0.961***
	(-22.042)	(-22.131)	(-21.018)	(-19.822)	(-19.780)	(-21.006)	(-20.664)
Principal (% of Total)	0.028***	0.027***	0.035***	0.027***	0.023***	0.031***	0.034***
	(30.071)	(28.512)	(29.385)	(26.327)	(23.352)	(26.599)	(29.437)
Debtor Age	0.004***	0.003***	0.003***	0.004***	0.003***	0.004***	0.003***
	(9.033)	(8.451)	(8.950)	(9.461)	(7.500)	(8.769)	(8.048)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,217,749	3,036,507	2,890,788	3,010,135	2,934,314	2,931,800	2,854,510
Pseudo R^2	0.222	0.221	0.226	0.225	0.223	0.227	0.214

This table reports logistic regression results for specifications that exclude a different year in each column. From left to right, the following years are excluded from the estimation sample: (1) 2013, (2) 2014, (3) 2015, (4) 2016, (5) 2017, (6) 2018, and (7) 2019. Included fixed effects: province, starting year-month of the recovery period, length of the recovery period (in months), and original creditor ID. Clustered (Province) co-variance matrix, t-stats in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.