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

Walter Distaso
ADIA, UAE
Imperial College Business School, United Kingdom

Wolfgang Lefever†
Department of Economics, Ghent University, Belgium

Angelo Luisi
Department of Economics, Ghent University, Belgium

Francesco Roccazzella
IESEG School of Management, Univ. Lille, CNRS, UMR 9221
- LEM - Lille Economie Management, F-59000 Lille, France

February 14, 2025

Abstract

Natural disasters are increasingly affecting the financial system. While most of the literature on natural disasters and credit risk focuses on the probability of default, very little is known about what happens after default. In this study, we combine two unique datasets to provide novel empirical evidence on the financial impact of wildfires through the loss given default channel. First, we determine Italian provinces' exposure to wildfires using geospatial data on burned areas derived from satellite imagery. Second, we exploit a proprietary dataset on defaulted consumer credits obtained from a third-party collection agency in Italy. Our results reveal a robust negative relationship between debtors' exposure to wildfires and the realized recovery rate. By focusing on wildfires that occur during the recovery process of already-defaulted consumer credits, we are able to isolate a loss given default channel, complementing existing evidence on default probabilities.

Keywords: Natural disasters; Wildfires; Consumer credit; LGD; Credit risk

*The authors thank Kris Boudt, Koen Inghelbrecht, Yasin Kürşat Önder, and the participants to the UGhent Banking and Finance Seminar for useful comments and remarks. Wolfgang Lefever acknowledges the support by the Research Foundation Flanders (FWO Vlaanderen) [grant number DOCT/006773]. Angelo Luisi acknowledges the support by the Research Foundation Flanders (FWO Vlaanderen) [grant number 12A0S25N].

†Corresponding author. Email address: wolfgang.lefever@ugent.be

1 Introduction

Climate change has significantly affected the frequency and the intensity of natural disasters (Bronstert, 2003; Bender et al., 2010; Turco et al., 2014; Bezner Kerr et al., 2022). Wildfires represent one of the most emblematic examples (Jolly et al., 2015; Cunningham et al., 2024). Over the period 2003-2019, the global burned area has increased by 15.8% (16.9% in the Mediterranean region) as a result of climate change, whose contribution has grown at an increasing rate (Burton et al., 2024). From 1984 to 2011, in the USA, the number of wildfires in the western region increased at a rate of 7 fires per year, and the total burned area at a rate of 355 squared kilometers per year (Dennison et al., 2014). In the European Union, 2017 and 2022 marked the worst two years in terms of burned hectares of natural land (San-Miguel-Ayanz et al., 2018, 2023).

Natural disasters affect the economic and financial conditions of households directly and indirectly. Direct impacts stem from immediate damage to assets such as property, infrastructure, and productive capital, as well as monetized effects on physical and mental health. Indirect costs include disruptions to economic activity, along with potential positive spillovers from production substitution and increased demand for reconstruction, affecting both short- and long-term economic recovery (Kousky, 2014; Botzen et al., 2019). These disruptions can impair borrowers' operations, reduce revenues, and weaken their debt repayment capacity, potentially leading to delinquency (i.e., higher Probability of Default, henceforth, PD). Furthermore, they reduce collateral values and future income streams, diminishing creditors' recovery potential in default situations (i.e., lower Recovery Rate, henceforth, RR). Consequently, natural disasters are likely to increase expected losses by raising not only the Probability of Default, but also the Loss Given Default (henceforth, LGD).[1] However, existing literature regarding the effect of natural disasters on household financial conditions mainly focuses on the former, without providing insights regarding what happens after default.

The main focus of this paper is assessing the impact of wildfires on the loss given default of consumer credits. Understanding this mechanism is crucial, given the growing relevance of natural disasters, and the dimension of households' debt. As of October 2024, aggregate U.S. household debt stands at USD 17.94 trillion, reflecting a USD 3.8 trillion increase since late 2019, just before the pandemic recession (Federal Reserve Bank of New York, Research

[1] LGD=1-RR.

and Statistics, 2024). In the Euro Area, consumer debt reached a record high of EUR 746.4 billion in December 2024, up from EUR 711.9 billion in March 2020, prior to the COVID pandemic.[2]

In order to analyse the LGD channel of wildfires, we rely on two unique datasets. First, we obtain acces to a proprietary dataset of over 3 million defaulted consumer credits in Italy from a third-party collection agency. Second, we use geospatial data on burned areas derived from satellite imagery to determine Italian provinces' exposure to wildfires. By combining these datasets, we have the unique opportunity of observing wildfires occurring during the recovery period (i.e., after the credit has defaulted and gone to the collection agency). Using a logistic regression model, we estimate the impact of wildfires on the recovery rate of defaulted consumer credits while controlling for credit and debtor characteristics. Our results reveal a robust negative relationship between debtors' exposure to wildfires, both during and before the recovery period, and the realized recovery rate. This effect is primarily driven by larger wildfire exposures and is significantly smaller in densely-populated areas.

2 Literature review

Our paper speaks to the vast literature analysing the economic and financial consequences of natural disasters, with a special focus on wildfires. Klomp and Valckx (2014) offer an extensive meta-analysis regarding the relationship between natural disasters and GDP growth, pointing at a growing negative effect emerging from several sources in existing literature. Moreover, natural disasters have a significant impact on labour market outcomes (Deryugina, 2022). Regarding wildfires, Meier et al. (2023) find a substantial reduction of GDP growth in Southern Europe, and lower regional employment in sectors related to retail and tourism. Furthermore, existing literature outlines how wildfires can have economic impact also indirectly, through smoke exposure (Borgschulte et al., 2024). Other economic impacts of wildfires include, among others, property prices (Nicholls, 2019), intangible and non-market costs (Johnston et al., 2021), forestry (Rego et al., 2013), and health costs (Johnston et al., 2021).

Natural disasters also have a profound impact on the financial system. Mallucci (2022),

[2]Data on credit for consumption vis-à-vis euro area households reported by MFIs in the euro area (stock) can be retrieved from the MFI balance sheets available from the ECB Statistical Data Warehouse `https://sdw.ecb.europa.eu/` with key BSI.M.U2.N.U.A21.A.1.U2.2250.Z01.E.

and Phan and Schwartzman (2024) find that extreme weather events impair governments borrowing capacity. Klomp (2017) finds that natural disasters affect public debt sustainability through a worsening of its public finances. Moreover, natural disasters are found to impact asset prices of firms, depending on their exposure (Pagano et al., 2023). Coherently, wildfires are also found to have important impact on public finances (Liao and Kousky, 2022; Jeon et al., 2024), and firms behaviours and financing conditions (Griffin et al., 2023; Tavor, 2024).

Our paper mainly contributes to the literature studying the effect of natural disasters on household finances. Existing research is increasingly pointing out that natural disasters and climate-related extreme events influence credit supply (Berg and Schrader, 2012; Cortés and Strahan, 2017; Nguyen and Wilson, 2018; Koetter et al., 2020), credit demand, households' financial decision-making (Gallagher and Hartley, 2017; Groen et al., 2020; Johar et al., 2022; del Valle et al., 2024), as well as credit scores and mortgage performance, in particular for financially constrained households (Ratcliffe et al., 2020; Billings et al., 2022). When focusing on the effect of wildfires on household finances, existing literature finds an increase in credit delinquency rates (Ho et al., 2023). It is noteworthy that natural disasters might also show negligible, or even a positive, impact on insured households (Biswas et al., 2023; Gallagher and Hartley, 2017; Gallagher et al., 2023). However, to the best of our knowledge, no studies bring evidence regarding the impact on the recovery once default took place.

Most of credit risk research focuses on credit scoring, which involves estimating default probabilities and their main drivers, as well as understanding credit cycles. For example, Djeundje and Crook (2018) find that incorporating account-specific effects and macroeconomic variables significantly enhances predictive accuracy for credit card defaults. Similarly, Malik and Thomas (2010) show that consumer default intensities for banking loans are influenced by business cycle indicators, and Carvalho et al. (2020) confirm that incorporating macroeconomic information improves the accuracy of models forecasting defaults of non-financial firms in the euro area, with GDP growth notably reducing default probabilities.

When it comes to identifying the main drivers of LGD, most of the literature has documented the central role of contract-specific variables (such as the debtors' age, recovery duration or the total amount to recover, and the incidence of fees and interests on the amount to principal). The legal environment may also play an important role. In the credit card industry, for instance, Fedaseyeu (2020) finds that consumer protection legislation governing third-party debt collection reduces the number of third-party debt collectors and increases the LGD on delinquent credit card loans.

Finally, the ability of households to repay defaulted credits should also be linked to their current financial situation. Low aggregate consumption and high unemployment rates often signal insufficient income and wealth, complicating loan repayment and reducing recovery values. There is no clear consensus on the relevance of macroeconomic and social environments as predictors of Loss Given Default (LGD). For instance, Bellotti and Crook (2012) analyse 55,000 defaulted UK credit card accounts from 1999 to 2005, and find that incorporating macroeconomic variables enhances the predictive power of recovery rate models. Specifically, higher interest rates and unemployment levels at default are associated with lower recovery rates, while higher earnings growth improves recoveries. Leow et al. (2014), instead, examine defaulted mortgages (1990–2002) and unsecured personal loans (1989–1999) and find that macroeconomic variables, such as net lending growth, disposable income growth, GDP growth, and unemployment rates, improves the prediction of mortgage loan recovery rates, but not personal loan recoveries. Beck et al. (2017) analyse German consumer credits for goods and services from 2004 to 2008, incorporating both idiosyncratic determinants (e.g., exposure at default and prior collection rates) and macroeconomic factors, such as GDP growth and regional unemployment rates. Only the latter consistently exhibits a negative effect on recovery rates. Distaso et al. (2024), instead, examine over six million Italian consumer credits managed by a third-party collection agency from 2007 to 2019, showing that macroeconomic and social factors significantly improve LGD forecasting. Key predictors include lower real economic activity, a higher cost-of-debt-to-GDP ratio, and heightened economic uncertainty, all of which are associated with higher LGD. Conversely, Nazemi et al. (2022) analyse 65,535 defaulted unsecured consumer credits acquired from a German telecommunications company (2010–2013) and find that including macroeconomic variables, such as provincial unemployment rates and excessive indebtedness rates, does not improve prediction accuracy.

At the aggregate level, evidence supports the relevance of business cycle dynamics for LGD. Calabrese (2012) identifies systematic relationships between average recovery rates and macroeconomic indicators—such as interest rates, GDP growth, unemployment, and aggregate default rates—based on a study of loan recovery processes in the Italian banking sector. Similarly, Caselli et al. (2008) demonstrate that LGD dynamics for household and

SME banking loans are shaped by distinct macroeconomic factors. For households, the most robust models link LGD to variables such as household default rates, unemployment, and consumption. Additional evidence comes from Konecny et al. (2017), who analyse retail banking in the Czech Republic, and highlight the significance of both lagged and contemporaneous macroeconomic effects, particularly in the context of consumer finance.

3 Data and Methodology

In the following sections, we provide a detailed description of the data and methodology used in our analysis. First, we discuss the datasets on defaulted consumer credits and wildfires in Italy. Next, we detail the empirical setup, including the data cleaning process, descriptive statistics, and the econometric framework used to analyze the relationship between wildfire exposure and recovery rates.

3.1 Defaulted consumer credits

Data on defaulted consumer credits (DCCs) is sourced from a proprietary, anonymised database managed by a third-party collector in Italy. This database contains DCCs originating from the telecommunications and utilities sectors, which third-party collectors are authorized to recover within a maximum period of $\Delta = 365$ days from the original creditor's mandate. Using data from a third-party collector, rather than a single original creditor, reduces biases from creditor-specific recovery procedures or industry of origin, while still allowing granular control over creditor and debtor characteristics across DCCs. The DCC contracts relate to natural persons and record their anonymised national registration number, enabling the extraction of gender, birth date as well as their main residency postal code. This allows each DCC to be matched to a specific region and province at the authorization date for recovery. Overall, the data spans from January 2013 to December 2019 and covers debtors across 18 out of 21 regions and 98 out of 110 provinces in Italy.[3]

Our variable of interest is the recovery rate (RR) and is defined as the outcome of the

[3]Debtor provinces are registered according to the 2016 version of the NUTS 3 classification, which contained 110 NUTS 3 regions in Italy. Following a reclassification of provinces in the Autonomous Region of Sardinia, the 2021 version of the NUTS classification contains 107 Italian NUTS 3 regions.

recovery process relative to the Total amount to Recover (TtR), i.e.,

$$RR_i = \frac{\text{sum of repayments}_i \text{ over the period } [\tau_i, \tau_i + \Delta_i]}{TtR_i \text{ at } [\tau_i]}, \tag{1}$$

where the collection process starts in τ_i when the collection agency receives the recovery mandate and its length Δ_i can vary across DCCs, but cannot exceed one year. We refer to $[\tau_i, \tau_i + \Delta_i]$ as the Recovery Period (RP) of the credit. Since wildfire exposure is measured at monthly frequency, we convert the length of the recovery period (observed in days) to months. To avoid including wildfires that occur beyond the actual recovery period, we round down to the number of full months.

The TtR includes the principal, interest, recovery fees, and administrative costs imposed by the original creditor. Therefore, the gross recovery rate RR reflects the recovery of principal, interest, and creditor-established fees but excludes handling fees charged by the third-party collector. These handling fees—typically a fixed fee plus a commission on recovered amounts—are defined in the bilateral contract, with payment by the original creditor at the collection period's end.

Following Distaso et al. (2024) and consistent with Bellotti and Crook (2012) for delinquent credit card accounts and Nazemi et al. (2022) for defaulted telecommunication credits, we consider DCCs for which recovery is initiated for the first time and measure the realized RR at the end of the collection period. If recovery is incomplete at this time (i.e., $RR < 1$ or no settlement), the original creditor may continue collection efforts in their name or assign a second mandate to a specialized firm. Amounts recovered from this second attempt would not be reflected in our observed RR. Additionally, third-party collector data lacks precise workout cost details (which vary by lender-collector contracts), so the RRs in our sample cannot be directly extrapolated as estimates of ultimate recovery. While the exact default date of a consumer credit contract is unknown, there is typically a 6-month delay in the telecommunications and utilities sectors between when the original creditor marks a credit as 'defaulted' and when it is transferred to the third-party collector. This timing aligns with the telecommunication contracts considered by Nazemi et al. (2022).

3.2 Wildfires data

We measure debtors' exposure to wildfires by calculating the burned area in the debtor's province of residence as a fraction of the total province area (BA). This variable is constructed by combining geospatial data on wildfires and administrative units. For wildfires, we use the Burnt Areas product provided by the European Forest Fire Information System (EFFIS),[4] which contains the exact delineations of the burn perimeters of wildfires in Europe at a daily frequency from 2001 onwards. This data is collected using a semi-automatic procedure to map fire-burned areas based on Moderate Resolution Imaging Spectroradiometer (MODIS) and Sentinel-2 satellite imagery. First, fires are mapped through an unsupervised procedure combining band thresholds, ancillary spatial datasets and fire news. These initial delineations are then verified and corrected through visual inspection. The output of this process can map burned areas with a size of around 30 hectares or larger and capture approximately 95% of the total burned area in the EU.

We use geospatial data on Italian provinces from the Nomenclature of Territorial Units for Statistics (NUTS) provided by the Geographic Information System of the Commission (GISCO).[5] NUTS is a harmonized classification system of EU countries' regions at three different levels. NUTS 1 divides each EU country into major socio-economic regions, NUTS 2 into basic regions for regional policies, and NUTS 3 into small regions for specific diagnoses. We focus on NUTS 3 regions as these correspond to provinces in Italy. We use the 2016 version of NUTS containing 110 Italian NUTS 3 regions as this matches the debtor provinces available in the defaulted consumer credits dataset. We calculate monthly wildfire exposure as the total burned area in each province in each month as a fraction of the total province area. For wildfires that affect multiple provinces, we only count the intersecting area between the burn perimeter and each province.

Our main variable of interest is the debtor's wildfire exposure during the recovery period (BA_{RP}), which we define as the sum of monthly exposures in the debtor's province of residence over the months of the recovery period. As the length of the recovery period is credit-specific and varies between 1 and 12 months, the number of months included in BA_{RP} also varies across credits. To guarantee a clean identification of the loss given default channel, it is important that the variable measuring wildfire exposure during the recovery period does not include any wildfires that occurred before the start of the recovery period. Such wildfires could cause debtors to default on their credit or induce the original creditor to enlist the services of the collection agency for an already-defaulted credit, both of which could pollute the estimation of an isolated LGD-channel. As we observe the month in which

[4] `https://forest-fire.emergency.copernicus.eu/about-effis/technical-background/rapid-damage-assessment`.

[5] `https://ec.europa.eu/eurostat/web/nuts/overview`.

the collection agency acquired the DCC but not the exact date, we define BA_{RP} as starting on the first day of the month after the acquisition of the DCC, removing the possibility of including any wildfires that happened before the recovery period.[6] We also calculate the debtor's wildfire exposure in the year before the start of the recovery period (BA_{-1y}) and the year before that (BA_{-2y}).

These measures of wildfire exposure treat all wildfires in the same way, without accounting for their location within the province. However, some wildfires may have a greater impact than others. To extend the baseline analysis, we examine whether the effects of wildfires vary based on their proximity to densely populated areas and man-made environments. This analysis relies on granular data on population density and land cover at the sub-province level. In the next section, we outline how we integrate these elements into the analysis.

3.2.1 Population density

In the baseline model, we combine geospatial data on provinces and wildfires to determine the monthly burned area in each province. To assess whether the impact of wildfires depends on the population density of the affected areas within a province, we incorporate data from each province's constituent municipalities. We refine the baseline measures described in the previous section by first determining wildfire exposure at the municipality level and then aggregating the results to the province. This enables us to incorporate the characteristics of the municipalities in which wildfires occur.

We obtain geospatial data on Local Administrative Units (LAUs), corresponding to Italian municipalities (*comuni*), from the GISCO.[7] Similar to NUTS, LAU is a harmonized classification system of EU countries' regions and essentially represents the next level of granularity after NUTS 3 regions (i.e., provinces in Italy). Importantly, NUTS and LAU are compatible systems in which LAUs serve as the building blocks of NUTS regions such that each Italian province is a combination of the underlying LAUs. We exploit this structure to

[6] This approach may lead us to include some additional days after the recovery period has already ended. However, given the fact that we round down the true length of the recovery period when converting it to full months, which has an offsetting effect, the overall impact is limited. Additionally, we verify that our results are robust to excluding the last month from BA_{RP}.

[7] `https://ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/local-administrative-units`.

compute the wildfire exposure of each province's constituent LAUs separately, allowing us to determine the population density of the affected areas within the province at a granular geographic level, before aggregating to the province level.

We start by computing the monthly wildfire exposure of each LAU as we did for the provinces and confirm that aggregating the LAU exposures to the province level creates a measure that closely resembles the original measure based on province geodata. Indeed, the largest deviation in burned area is 17 hectares, or 3.4% of the average burned area in months with at least some wildfires (and 1.8% of the burned area in question). We also confirm that the regression results for the main specification using the original wildfire measures or the LAU-based measures are practically identical.

On average, an Italian province is composed of 72 LAUs. For each LAU, we observe the population density and degree of urbanization. The degree of urbanization is a classification system created by the GISCO that uses geographical contiguity and population density to classify each LAU into one of the following three categories: cities, towns and suburbs, and rural areas.[8] Using these LAU characteristics, we employ two approaches to evaluate whether the impact of wildfires in a province depends on the population of the affected LAUs within that province.

We can interpret the wildfire exposure variable from the main specification, i.e., the fraction of the total area of province p that was burned by wildfires in month s, as a proxy for the fraction of the population in the province that was affected by wildfires:

$$BA_{p,s} = \frac{BA(km^2)_{p,s}}{Area(km^2)_p} = \frac{\frac{BA(km^2)_{p,s}}{Area(km^2)_p} \times Pop_{p,s}}{Pop_{p,s}}. \tag{2}$$

We can refine this proxy by exploiting the fact that we observe both wildfire exposures and population densities at the LAU level. As shown in eq. 3, we do this by calculating the numerator of eq. 2 separately for each LAU m belonging to province p before aggregating to the province level, essentially weighting the burned areas within a province by the population density of the municipality in which they occur.

$$BA_{p,s} = \frac{\sum(\frac{BA(km^2)_{m,s}}{Area(km^2)_m} \times Pop_{m,s})}{Pop_{p,s}}. \tag{3}$$

Alternatively, we determine the share of the total burned area in the province that occurred in LAUs categorized as *cities* according to the degree of urbanization classification.

[8] `https://ec.europa.eu/eurostat/web/gisco/geodata/population-distribution/degree-urbanisation`.

We interact this measure with the wildfire exposure variables to determine whether wildfires that occur in or near cities have a different effect from those affecting towns and suburbs or rural areas.

3.2.2 Land cover

As a second extension, we examine whether wildfires affecting man-made environments have a different impact than those affecting natural land. To do so, we calculate the share of the total burned area within each province that occurred in man-made environments. We then interact this variable with the wildfire exposure measures to test for significant differences in the effect.

We collect CORINE Land Cover (CLC) data from the Copernicus Land Monitoring Service.[9] The CLC database was established to standardize land cover data collection across Europe. It is primarily derived from ortho-corrected high-resolution satellite imagery, supplemented by topographic maps, ortho-photos, and ground survey data (Büttner et al., 2021). The database classifies land cover into 44 categories at a 100-meter by 100-meter resolution and is updated every six years. We use raster files from the 2006, 2012, and 2018 editions.

For each wildfire polygon in the burned areas dataset (split across province boundaries if the wildfire affected several provinces), we compute the share of the total burned area that occurred in the "Artificial areas" CLC category, which we refer to as man-made environments. This category includes the following subcategories: (i) urban fabric, (ii) industrial, commercial and transport units, (iii) mine, dump and construction sites, and (iv) artificial non-agricultural vegetated areas.[10] Aggregating this measure to the province level, we calculate the share of the total burned area in the province that occured in man-made environments. We always determine the land cover of the burned area using the most recent version of the land cover dataset that could not have been affected by the occurrence of that wildfire. We use the 2006 version of the CLC database for wildfires up to 31 Dec 2012, the 2012 version for wildfires between 1 Jan 2013 and 31 Dec 2018, and the 2018 version for wildfires from 1 Jan 2019 onwards.

[9] `https://land.copernicus.eu/en/products/corine-land-cover`.

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

3.3 Data processing and descriptive statistics

We now outline the empirical setup, first detailing the data-cleaning process and then moving on to descriptive statistics of the final sample.

In line with Bellotti and Crook (2012); Nazemi et al. (2022); Distaso et al. (2024), we focus on defaulted credits with a maximum recovery period duration of one year. We count 3,373,182 observations, and to further enhance the homogeneity of the dataset and prevent results from being disproportionately influenced by outliers, we filter out observations where the total amount to recover is below 20 EUR or above 5,000 EUR, the principal-to-total ratio exceeds 1, or the debtor is over 80 years old. Finally, since the recovery period is measured in full months, DCCs with a recovery period shorter than one month are excluded from the sample, as they cannot be assigned a wildfire exposure during the recovery period. Figure 1 highlights that the dataset exhibits a highly bimodal distribution of recovery rates, with 88% of DCCs having recovery rates of exactly 0 or 1, consistent with previous studies on recovery rates in the consumer credit industry (Thomas et al., 2012; Nazemi et al., 2022; Distaso et al., 2024). Consequently, for the main analysis, we exclude the remaining 12% of DCCs with continuous recovery rates (values between 0 and 1) from the sample, as a binary outcome model is more appropriate for the majority of observations, and no clear threshold exists for converting continuous values to binary outcomes. The results remain robust when these DCCs are included, with recovery rates greater (less) than 0.5 mapped to 1 (0) as demonstrated in Section A.3. As a result, the final sample consists of 3,049,627 defaulted consumer credits between 2013 and 2019 across 98 (out of 110) Italian provinces, representing a total defaulted debt of over EUR 1.2 billion. About 19% of the credits, making up 8.8% of the total owed amount (EUR 107 million), was successfully recovered.[11] The large share of unrecovered DCCs is in line with the statistics reported by Thomas et al. (2012) for third-party collection. 59% of DCCs originate from the telecommunications sector and 41% from the utilities sector.

Descriptive statistics for the DCC characteristics are reported in Table 1. The average owed amount is about 400 EUR (median 250 EUR), with the principal making up over 90% of the total (the rest being interest and ancillary fees). The recovery period spans an average of 4 months and rarely extends beyond 6 months (less than 5% of observations).

[11] The owed amount in the dataset including DCCs with a non-binary recovery rate totals almost EUR 1.4 billion, of which 14% (EUR 195 million) was recovered.

Table 2 presents descriptive statistics of the wildfire exposure variables. About 22% of the observations in the sample had some wildfire exposure during the recovery period. For the BA variables capturing wildfire exposure one and two years before the recovery period, this percentage rises to respectively 45% and 42%. As the "lag" variables always include 12 months whereas the recovery period BA variable spans an average of 4 months, they have more observations with some wildfire exposure. Conditional on the occurrence of at least one wildfire, an average of 0.37% of the total province area was burned during the recovery period, and 0.53% and 0.66% during respectively the first and second year before the recovery period. The lower median values indicate that the average is pushed up by some very large values. The maximum value of 4.10% reflects the wildfires of July and August 2017 in the province of Naples, which destroyed large portions of woodland surrounding the Vesuvius volcano.[12]

3.4 Econometric framework

The logistic regression model is particularly well-suited for our analysis as the dependent variable is bounded between 0 and 1. Unlike linear regression, which may produce predictions outside this range, logistic regression or logit ensures that predicted values remain within the $[0, 1]$ interval, making it ideal for modeling the probability of default or recovery rates (Lawrence et al., 1992; Jiménez and Saurina, 2004; Thomas et al., 2012; Imbierowicz and Rauch, 2014).

Specifically, we estimate the effect of wildfire exposure on the probability to recover defaulted consumer credits using logistic regression of the form:

$$RR_{i,p,t,c} = \beta_{RP} BA_{p,RP} + \gamma_1 BA_{p,-1y} + \gamma_2 BA_{p,-2y} + CV_i + \tau_t + \rho_p + \zeta_c + \epsilon_{i,p,t,c}, \qquad (4)$$

where $RR_{i,p,t,c}$ is the realized recovery rate for defaulted consumer credit i from province p with original creditor c whose recovery period started in month t. The main variable of interest, $BA_{p,RP}$, measures the total burned area in province p during the recovery period as a fraction of the total province area. $BA_{p,-1y}$ and $BA_{p,-2y}$ measure the burned area in province p (as a fraction of total province area) during respectively the year before the start of the recovery period and the year before that. We control for the following credit and debtor characteristics: total to recover (ln), share of the principal in total to recover

[12] https://www.esa.int/ESA_Multimedia/Images/2017/07/Vesuvius_on_fire.

(as opposed to interest and ancillary fees), debtor age, and debtor sex (dummy). We also include dummy variables for the province of the debtor, the starting month of the recovery period, the length of the recovery period in months, and the original creditor ID. Standard errors are clustered at the province level.

4 Results

4.1 Baseline model

We present the estimation results in Table 3. Column 1 reports the regression coefficients and t-statistics, while Column 2 provides the corresponding odds ratios. The odds ratios are calculated as the exponential of the regression coefficients and, in our logistic regression framework, represent the ratio of the odds of observing a successful recovery, i.e., $RR = 1$, associated with a one-unit increase in the corresponding regressor.

β_{RP} is negative and significant at 0.1%, indicating that higher wildfire exposure during the recovery period is associated with a lower recovery rate. The coefficient of -0.110 corresponds to an odds ratio of 0.896, meaning that a 1%-point increase in the total burned area of the province during the recovery period (as a fraction of total province area) decreases the odds of recovery by about 10%. Similarly, the negative coefficients on the lagged wildfire exposure variables, γ_1 and γ_2, significant at respectively 1% and 0.1%, indicate that higher wildfire exposure in the years preceding the start of the recovery period is also associated with a lower recovery rate. It is important to note that a value of 1 for the wildfire exposure measures, indicating a burned area equal to 1% of the total province area, constitutes a fairly severe exposure. Out of all the credits in our sample with some wildfire exposure during the recovery period (i.e., $BA_{RP} > 0$), about 9.5% have a value greater than or equal to 1. For BA_{-1y} and BA_{-2y}, roughly 14.5% and 20.5% of credits with some exposure have a value greater than or equal to 1. To illustrate the magnitude of the estimated effects at different levels of wildfire exposure, columns 3, 4, and 5 report the odds ratios for the 10th, 50th and 90th percentile values of the (non-zero) wildfire exposures.

Our findings on the control variables align with the literature on the determinants of the LGD of defaulted consumer credits (Nazemi et al., 2022; Thomas et al., 2012; Distaso et al., 2024). Specifically, we identify a significant negative relationship between the recovery rate and the total amount to recover, while a larger share of principal in the total amount to recover is associated with a higher recovery rate. In contrast, the estimated positive relationship between recovery rate and debtor age differs from the negative relationship reported by Nazemi et al. (2022).

We perform two checks to verify that β_{RP} is capturing the effect of wildfires that occur *during* the recovery period. First, as discussed in Section 3.2, our measure of wildfire exposure during the recovery period (BA_{RP}) may include some days beyond the end of the recovery period. To ensure that the estimated effect is not driven by wildfires occurring after the recovery period, we exclude the entire last month from BA_{RP}, eliminating all possible overmeasurement of wildfire exposure. In Appendix A.1, we show that our result is robust to this change. The second check relates to the recurring nature of wildfires. Debtors who were exposed to wildfires during the recovery period had a high probability of also being exposed to wildfires in the years preceding the recovery period[13]. While BA_{RP} only captures wildfires that occurred after the debtor had already defaulted by construction and can only affect recovery rates through loss given default, past wildfire exposure may also have an impact by affecting default rates. Therefore, to ensure that β_{RP} captures a loss given default effect, it is important to account for the relationship between wildfire exposure during and before the recovery period. In the baseline model, we do so by including BA_{-1y} and BA_{-2y} as control variables in the regression. To completely eliminate any remaining impact of past wildfire exposure on the realized recovery rate that may not be captured by the control variables, we estimate the model on the subset of credits without any wildfire exposure in the two years preceding the recovery period. In Appendix A.2, we show that the negative effect of BA_{RP} remains significant.

We perform several other checks, all of which reinforce the baseline results. In Appendix A.3, we include the DCCs with a non-binary recovery rate in the estimations by converting their recovery rate to 0 or 1. Second, we account for regional heterogeneity by controlling for region- and province-specific macro-economic and social characteristics (Appendix A.4) and by including province-specific time effects (Appendix A.5). Third, in Appendix A.6, we show that our results are robust to removing the largest and most frequent wildfire exposure values from the estimation, as well as all credits originating from Naples (the province with the most wildfire-exposed credits in the sample).

[13]The correlation between BA_{RP} and the yearly lags is 0.32 for BA_{-1y} and 0.24 for BA_{-2y}. 75% of observations with some wildfire exposure during the recovery period ($BA_{RP} > 0$) also had some exposure in the preceding year ($BA_{-1y} > 0$), and 65% in the year before that ($BA_{-2y} > 0$)

In the following sections, we extend the baseline model to explore potential heterogeneity in the effect of wildfires on recovery rates. In Section 4.2, we evaluate whether the scale of the wildfire exposure affects its impact on recovery rates by separately estimating the effect of the largest 50% and smallest 50% of exposure values. In Section 4.3, we explore how the characteristics of the burnt areas, particularly their proximity to densely-populated areas and man-made environments, may affect the negative relationship with recovery rates.

4.2 Wildfire severity

Measuring wildfire exposure as a continuous variable allows us to avoid making arbitrary decisions about what qualifies as a natural disaster. By estimating the effect of the magnitude of wildfires relative to the total area of the province, we take a more agnostic stance on how and which wildfires can have an impact. However, a limitation of this method is that the BA variable often takes on very small values, capturing minor wildfires that are unlikely to significantly affect recovery rates. To ensure that our results are not (only) driven by small wildfires, we decompose the BA variable into two separate variables: one containing above-median values and the other containing below-median values, thus isolating the effects of larger (smaller) wildfires. Column 1 of Table 4 reports the results of a regression that only includes the above-median BA variables, essentially censoring all below-median wildfire exposures to zero. Results are very similar to the baseline specification. The model in column 2 includes both the above-median and below-median BA variables. These results show that larger wildfire exposures are driving the negative effects, while smaller wildfire exposures have no significant effect.

4.3 Proximity to densely populated areas and man-made environments

We investigate whether the relationship between recovery rates and wildfire exposure in the debtor's province varies with the population density of affected municipalities and the share of the burned area that affected man-made environments, such as urban fabrics, industrial, commercial, and transport units, mines, dumps, construction sites, and other artificial non-agricultural or non-forested areas.

As described in Section 3.2.1, we map wildfire exposure at the municipality level and aggregate it to the province level to account for the population density of municipalities within each province. First, we verify that aggregating LAU-level wildfire exposures to the province level without applying any weighting closely mimics the province-level wildfire exposures from the main specification. Columns 1 and 2 of Table 5 compare the results of the same regression model using the baseline province-level BA measures and the LAU-based aggregated BA measures, respectively. The results are nearly identical, alleviating concerns that the estimations incorporating municipality population characteristics are not comparable to the main specification.

Column 3 presents regression results using the modified wildfire exposure measure that assigns a higher (lower) weight to wildfires that occur in municipalities with a higher (lower) population density. The estimated effect of wildfire exposure during the recovery period changes very little compared to the unweighted model (column 2). Interestingly, the coefficient on BA_{-2y} becomes insignificant and each of the coefficients shrinks in size.

In a second approach, we explicitly estimate whether the effect of wildfires differs in densely-populated areas. Specifically, column 4 uses the BA measures based on the aggregated LAU-level exposures (as in column 2) but includes a term that interacts each wildfire measure with the share of the total burned area that occurred in city municipalities (according to the degree of urbanization classification). The coefficients on the BA variables estimate the effect of wildfires occurring in non-city municipalities (towns, suburbs and rural areas) and the coefficients on the interaction terms indicate whether wildfires that affect cities have a different effect. The interaction coefficients for the recovery period and first lag are positive and significant at 5%, indicating that the effect of wildfires that occur in city municipalities is less negative compared to wildfires that occur in towns, suburbs and rural municipalities.

We then investigate whether the significant negative relationship between wildfires and recovery rates depends on the proximity to man-made environments, determined by the land cover types of the burned areas in the province (column 5). Similar to column 4, this model includes the main province-level wildfire exposures and an interaction term measuring the share of the total burned area that occurred in man-made environments. The coefficients on the main BA variables estimate the effect of wildfires that occur in the other land cover types (mostly forests and agricultural land) and the interaction terms estimate the difference in effect for wildfires occurring in built-up areas. Similar to the results reported in column 4, the interaction coefficients for the recovery period and first lag are positive and significant at 5%, indicating a significantly less negative effect of wildfires that occur in built-up areas.

4.4 Discussion

A borrower's ability to repay debt depends on factors such as income, cash flow, and asset liquidity, which are particularly critical for unsecured credit, such as telecommunications and utilities, that lack collateral. In Section 4.1, we bring new empirical evidence that higher wildfire exposure before and during the recovery period is associated with a lower recovery rate. There are multiple ways in which wildfires could affect households' financial situation. For instance, wildfires can have a *direct* impact by destroying residential properties (Biswas et al., 2023), affecting their health (Deryugina et al., 2019; Johnston et al., 2021), or affecting their income (Borgschulte et al., 2024). *Indirectly*, wildfires have been shown to affect regional economic outcomes in southern Europe (Meier et al., 2023), which in turn could affect defaulted debtors' ability to repay (Bellotti and Crook, 2012; Distaso et al., 2024).

Our baseline model indicates that the larger the wildfire relative to the area of the province, the greater the negative impact of the recovery rate. In Section 4.2, we find that this effect is primarily driven by larger exposures to wildfires. When dividing the wildfire exposure variables at the median, only the above-median values have a significant effect, suggesting that wildfires must reach a certain scale before having a meaningful impact.

Although our defaulted consumer credit database does not allow us to pinpoint the exact channel through which wildfires shape the recovery rate distribution, our findings suggest that the negative impact of wildfire exposure is mitigated by proximity to densely populated areas and man-made environments.

One possible explanation is that *city* economies are highly diversified, reducing the risk of widespread income losses following a disaster. In contrast, lower-density areas rely on a few industries or services, and access to financial services may be limited. Therefore, income loss and financial constraints following a natural disaster can persist longer and, in turn, hinder third-party collectors in pursuing recoveries. Moreover, despite wildfires in densely populated areas potentially causing greater property damage, they may trigger a stronger emergency response in terms of both suppression efforts and financial aid. This could mitigate the economic impact of natural disasters and safeguard household finances, thereby enhancing collectors' ability to recover debts.

This aligns with findings from Gallagher et al. (2023), who show that individuals living in census blocks that suffered severe tornado damage have a reduction in credit card debt and bill delinquencies if disaster aid is available. Further, direct property damage could provide debtors with an influx of liquidity through insurance payouts, increasing their ability to repay defaulted debt in the short term. Previous studies have found evidence of homeowners using insurance payouts to pay down outstanding debt instead of rebuilding their property after wildfires (Biswas et al., 2023) and hurricane-related flooding (Gallagher and Hartley, 2017).

5 Conclusion

Climate change is significantly increasing the frequency and intensity of natural disasters, with wildfires being a prominent example. Natural disasters can affect household finances both directly—through asset destruction and health costs—and indirectly, by disrupting local economic activity, thus weakening borrowers' repayment capacity. Therefore, natural disasters should not only raise the likelihood of delinquency but also affect recovery rate after default. While existing literature focuses primarily on probability of default, we provide empirical evidence on the negative financial impact of wildfires through a loss given default channel.

In our analysis, we combine a unique dataset containing more than 3 million defaulted consumer credits originating from the telecommunications and utility sectors in Italy with geospatial data on burned areas derived from satellite imagery. Using a logistic regression model, we show that debtors' exposure to wildfires during the recovery process decreases the realized recovery rate. This effect is primarily driven by larger-scale wildfires. Proximity to densely-populated areas and man-made environments, such as urban areas and industrial, commercial and transport sites, appear to mitigate the negative impact. However, data constraints prevent us from identifying specific economic transmission channels. Future research using granular household-level data could offer deeper insights into these channels.

References

Beck, T., J. Grunert, W. Neus, and A. Walter (2017). What determines collection rates of debt collection agencies? *Financial Review 52*(2), 259–279.

Bellotti, T. and J. Crook (2012, January). Loss given default models incorporating macroeconomic variables for credit cards. *International Journal of Forecasting 28*(1), 171–182.

Bender, M. A., T. R. Knutson, R. E. Tuleya, J. J. Sirutis, G. A. Vecchi, S. T. Garner, and I. M. Held (2010, January). Modeled impact of anthropogenic warming on the frequency of intense atlantic hurricanes. *Science 327*(5964), 454–458.

Berg, G. and J. Schrader (2012, October). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation 21*(4), 549–568.

Bezner Kerr, R., T. Hasegawa, R. Lasco, I. Bhatt, D. Deryng, A. Farrell, H. Gurney-Smith, H. Ju, S. Lluch-Cota, F. Meza, G. Nelson, H. Neufeldt, and P. Thornton (2022). *Food, Fibre, and Other Ecosystem Products*, pp. 713–906. Cambridge, UK and New York, USA: Cambridge University Press.

Billings, S. B., E. A. Gallagher, and L. Ricketts (2022). Let the rich be flooded: The distribution of financial aid and distress after hurricane harvey. *Journal of Financial Economics 146*, 797–819.

Biswas, S., M. Hossain, and D. Zink (2023). California wildfires, property damage, and mortgage repayment. *Federal Reserve Bank of Philadelphia Working Paper*.

Borgschulte, M., D. Molitor, and E. Y. Zou (2024, 11). Air pollution and the labor market: Evidence from wildfire smoke. *Review of Economics and Statistics*, 1–46.

Botzen, W. J. W., O. Deschenes, and M. Sanders (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy 13*(2), 167–188.

Bronstert, A. (2003, May). Floods and climate change: Interactions and impacts. *Risk Analysis 23*(3), 545–557.

Burton, C., S. Lampe, D. I. Kelley, W. Thiery, S. Hantson, N. Christidis, L. Gudmundsson, M. Forrest, E. Burke, J. Chang, H. Huang, A. Ito, S. Kou-Giesbrecht, G. Lasslop, W. Li, L. Nieradzik, F. Li, Y. Chen, J. Randerson, C. P. O. Reyer, and M. Mengel (2024, 11). Global burned area increasingly explained by climate change. *Nature Climate Change 14*, 1186–1192.

Büttner, G., B. Kosztra, G. Maucha, R. Pataki, S. Kleeschulte, G. Hazeu, M. Vittek, C. Schröder, and A. Littkopf (2021). Corine land cover - product user manual.

Calabrese, R. (2012). Predicting bank loan recovery rates with a mixed continuous-discrete model. *Applied Stochastic Models in Business and Industry 30*(2), 99–114.

Carvalho, P. V., J. D. Curto, and R. Primor (2020, September). Macroeconomic determinants of credit risk: Evidence from the eurozone. *International Journal of Finance & Economics 27*(2), 2054–2072.

Caselli, S., S. Gatti, and F. Querci (2008). The sensitivity of the loss given default rate to systematic risk: New empirical evidence on bank loans. *Journal of Financial Services Research 34*(1), 1–34.

Cortés, K. R. and P. E. Strahan (2017, July). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics 125*(1), 182–199.

Cunningham, C. X., G. J. Williamson, and D. M. Bowman (2024). Increasing frequency and intensity of the most extreme wildfires on earth. *Nature ecology & evolution 8*(8), 1420–1425.

del Valle, A., T. Scharlemann, and S. Shore (2024, January). Household financial decision-making after natural disasters: Evidence from hurricane harvey. *Journal of Financial and Quantitative Analysis 59*(5), 2459–2485.

Dennison, P. E., S. C. Brewer, J. D. Arnold, and M. A. Moritz (2014). Large wildfire trends in the western united states, 1984–2011. *Geophysical Research Letters 41*(8), 2928–2933.

Deryugina, T. (2022). Economic effects of natural disasters. *IZA World of Labor*.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review 109*, 4178–4219.

Distaso, W., F. Roccazzella, and F. Vrins (2024, December). Business cycle and realized losses in the consumer credit industry. *European Journal of Operational Research*.

Djeundje, V. B. and J. Crook (2018, December). Incorporating heterogeneity and macroeconomic variables into multi-state delinquency models for credit cards. *European Journal of Operational Research 271*(2), 697–709.

Fedaseyeu, V. (2020). Debt collection agencies and the supply of consumer credit. *Journal of Financial Economics 138*(1), 193–221.

Federal Reserve Bank of New York, Research and Statistics (2024, November). Quarterly report on household debt and credit: 2024 Q3.

Gallagher, J. and D. Hartley (2017, August). Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy 9*(3), 199–228.

Gallagher, J., D. Hartley, and S. Rohlin (2023). Weathering an unexpected financial shock: The role of federal disaster assistance on household finance and business survival. *Journal of the Association of Environmental and Resource Economists*.

Griffin, P. A., Y. Jiang, and E. Y. Sun (2023). Threatened by wildfires: What do firms disclose in their 10-ks? *Journal of Business Finance & Accounting 50*(5-6), 895–942.

Groen, J. A., M. J. Kutzbach, and A. E. Polivka (2020, July). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics 38*(3), 653–685.

Ho, A. T., K. P. Huynh, D. T. Jacho-Chávez, and G. Vallée (2023, May). We didn't start the fire: Effects of a natural disaster on consumers' financial distress. *Journal of Environmental Economics and Management 119*, 102790.

Imbierowicz, B. and C. Rauch (2014, March). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance 40*, 242–256.

Jeon, W., L. Barrage, and K. J. Walsh (2024). Pricing climate risks: Evidence from wildfires and municipal bonds. Technical report, CESifo Working Paper.

Jiménez, G. and J. Saurina (2004, September). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking & Finance 28*(9), 2191–2212.

Johar, M., D. W. Johnston, M. A. Shields, P. Siminski, and O. Stavrunova (2022, April). The economic impacts of direct natural disaster exposure. *Journal of Economic Behavior & Organization 196*, 26–39.

Johnston, D. W., Y. K. Önder, M. H. Rahman, and M. A. Ulubaşoğlu (2021, 12). Evaluating wildfire exposure: Using wellbeing data to estimate and value the impacts of wildfire. *Journal of Economic Behavior and Organization 192*, 782–798.

Johnston, F. H., N. Borchers-Arriagada, G. G. Morgan, B. Jalaludin, A. J. Palmer, G. J. Williamson, and D. M. Bowman (2021, 1). Unprecedented health costs of smoke-related pm2.5 from the 2019–20 australian megafires. *Nature Sustainability 4*, 42–47.

Jolly, W. M., M. A. Cochrane, P. H. Freeborn, Z. A. Holden, T. J. Brown, G. J. Williamson, and D. M. Bowman (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature communications 6*(1), 7537.

Klomp, J. (2017, May). Flooded with debt. *Journal of International Money and Finance 73*, 93–103.

Klomp, J. and K. Valckx (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change 26*, 183–195.

Koetter, M., F. Noth, and O. Rehbein (2020, July). Borrowers under water! rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation 43*, 100811.

Konecny, T., J. Seidler, A. Belyaeva, and K. Belyaev (2017). The time dimension of the links between loss given default and the macroeconomy. *Czech Journal of Economics and Finance 67*(6), 462–491.

Kousky, C. (2014, November). Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics 46*, 576–592.

Lawrence, E. C., L. Smith, and M. Rhoades (1992, April). An analysis of default risk in mobile home credit. *Journal of Banking & Finance 16*(2), 299–312.

Leow, M., C. Mues, and L. Thomas (2014). The economy and loss given default: evidence from two UK retail lending data sets. *Journal of the Operational Research Society 65*(3), 363–375.

Liao, Y. and C. Kousky (2022). The fiscal impacts of wildfires on california municipalities. *Journal of the Association of Environmental and Resource Economists 9*(3), 455–493.

Malik, M. and L. C. Thomas (2010). Modelling credit risk of portfolio of consumer loans. *Journal of the Operational Research Society 61*(3), 411–420.

Mallucci, E. (2022, November). Natural disasters, climate change, and sovereign risk. *Journal of International Economics 139*, 103672.

Meier, S., R. J. Elliott, and E. Strobl (2023, 3). The regional economic impact of wildfires: Evidence from southern europe. *Journal of Environmental Economics and Management 118*.

Nazemi, A., H. Rezazadeh, F. J. Fabozzi, and M. Hochstotter (2022, January). Deep learning for modeling the collection rate for third-party buyers. *International Journal of Forecasting 38*(1), 240–252.

Nguyen, L. and J. O. S. Wilson (2018, December). How does credit supply react to a natural disaster? evidence from the indian ocean tsunami. *The European Journal of Finance 26*(7–8), 802–819.

Nicholls, S. (2019, 9). Impacts of environmental disturbances on housing prices: A review of the hedonic pricing literature. *Journal of Environmental Management 246*, 1–10.

Pagano, M., C. Wagner, and J. Zechner (2023). Disaster resilience and asset prices. *Journal of Financial Economics 150*(2), 103712.

Phan, T. and F. Schwartzman (2024, November). Climate defaults and financial adaptation. *European Economic Review 170*, 104866.

Ratcliffe, C., W. Congdon, D. Teles, A. Stanczyk, and C. Martín (2020, November). From bad to worse: Natural disasters and financial health. *Journal of Housing Research 29*(sup1), S25–S53.

Rego, F., G. Louro, and L. Constantino (2013, 4). The impact of changing wildfire regimes on wood availability from portuguese forests. *Forest Policy and Economics 29*, 56–61.

San-Miguel-Ayanz, J., T. Durrant, R. Boca, G. Libertà, A. Branco, D. de Rigo, D. Ferrari, P. Maianti, T. A. Vivancos, H. Costa, F. Lana, P. Löffler, D. Nuijten, A. C. Ahlgren, and T. Leray (2018). Forest fires in europe, middle east and north africa 2017.

San-Miguel-Ayanz, J., T. Durrant, R. Boca, P. Maianti, G. Liberta‘, D. J. F. Oom, A. Branco, D. D. Rigo, M. Suarez-Moreno, D. Ferrari, E. Roglia, N. Scionti, M. Broglia, M. Onida, A. Tistan, and P. Loffler (2023). Forest fires in europe, middle east and north africa 2022.

Tavor, T. (2024). Assessing the financial impacts of significant wildfires on us capital markets: sectoral analysis. *Empirical Economics*, 1–34.

Thomas, L. C., A. Matuszyk, and A. Moore (2012, 1). Comparing debt characteristics and lgd models for different collections policies. *International Journal of Forecasting 28*, 196–203.

Turco, M., M.-C. Llasat, J. von Hardenberg, and A. Provenzale (2014, July). Climate change impacts on wildfires in a mediterranean environment. *Climatic Change 125*(3–4), 369–380.

A Appendix

A.1 Exclude last month of recovery period from wildfire exposure

In the main analysis, we define the recovery period as starting on the first day of the month after the acquisition of the defaulted credit by the collection agency. This ensures that our measure of wildfire exposure during the recovery period, BA_{RP}, does not capture any wildfires that happened during the month in which the credit was acquired but before the recovery period had started. A potential drawback of this approach is that, for the last calendar month of the recovery period, BA_{RP} may capture some wildfires that happened after the recovery period had already ended. This is partly offset by rounding down to full months when converting the length of the recovery period from days to months (to match the monthly frequency of the wildfire exposures dataset).

To eliminate any remaining concerns of BA_{RP} potentially capturing wildfires that happened after the recovery period had already ended, we exclude the last month of the recovery period from the exposure variable (BA_{RP-1m}). As a result, we can no longer determine the exposure of credits with a recovery period of one month. These credits, representing about 7.3% of the sample size, are dropped from the estimation. First, we re-estimate the baseline model for the subset of credits with a recovery period of at least two months. Results are presented in column 1 of Table 6. The estimated effect for BA_{RP} is similar in magnitude and significance to the full sample result, while the significance of the lagged wildfire measures decreases noticeably, with only the first lag remaining significant at 5%. Column 2 presents the results from the estimation using the restricted measure of wildfire exposure during the recovery period, BA_{RP-1m}. The results are very similar to column 1, confirming that the baseline results are not driven by wildfires that happened outside of the recovery period.

A.2 No recent wildfires

In the main specification, we control for debtor's wildfire exposure before the recovery period using two variables capturing total burned area in the 12 months preceding the start of the recovery period, and the 12 months before that. Given that wildfires are more likely to occur in areas that also experienced wildfires in the past (due to the region-specific nature of wildfires), we include these lags to ensure that the estimate for BA_{RP} captures the loss-given-default effect of wildfires. In other words, we isolate the effect on recovery rate of wildfires that occur *during* the recovery period by controlling for the potentially negative effects on recovery rates of wildfires that happened before start of the recovery period. While our analysis indicates that these pre-RP wildfires also negatively affect recovery rates, we mainly focus on wildfires during the RP as this allows for a precise identification of the loss given default channel.

As a robustness check, we estimate the model using only DCC with no wildfire exposure at all during the two years preceding the recovery period. This eliminates any potential bias stemming from the included one-year and two-year lagged wildfire variables in the main specification not perfectly controlling for the impact of pre-RP wildfires on recovery rates. Table 7 shows that the estimated effect of BA_{RP} remains significant at 5% and has a substantially greater magnitude than the main specification. Note that filtering the sample to DCCs with no recent wildfire exposure dropped over 55% of observations. Importantly, the geographic distribution of the sample shifted north as southern areas were much more likely to have experienced wildfires in the recent past, shifting the distribution of BA_{RP} downward. Hence, the estimated magnitude of the effect is not directly comparable to the main specification.

A.3 Include DCCs with non-binary RR

In the main specification, we only keep DCCs with a realized recovery rate equal to 0 or 1, dropping about 12% of DCCs for which the collection agency was able to recover a part, but not all, of the owed amount. This is motivated by the fact that the vast majority of DCCs are either recovered in full, or not at all, making logistic regression the preferred estimation method but necessitating all outcomes to be 0 or 1. As a robustness check, we convert the recovery rates of those DCCs with a non-binary recovery rate to 0 or 1 and include them in the regressions. In Table 8, we present the results when converting the recovery rate to 1 if the continuous value is greater than or equal to 0.50 (column 2) or greater than 0 (column 3). Column 1 repeats the baseline results for comparison. BA_{RP} remains significant at 0.1%, though the estimated magnitude of the effect shrinks somewhat. The negative relationship between the recovery rate and Total to Recover shrinks considerably. Unsurprisingly, DCCs with a higher Total to Recover are more likely to have a non-binary realized recovery rate in our dataset. By removing these DCCs from the sample in the main specification, the estimated effect of Total to Recover may be biased downward. The model fit, as measured by pseudo R^2, drops substantially when including DCCs with (converted) non-binary recovery rate.

A.4 Regional control variables

The main specification includes monthly dummies, capturing time effects at the national level. In this section, we account for time variation at the sub-national level using macroeconomic and social control variables. We include these control variables at the level of Italian regions (NUTS 2) and provinces (NUTS 3) in separate regressions. For the region-level regressions, we include the natural log of the GDP per capita and the unemployment rate as macro controls and the homicide rate, assault rate, and poverty risk rate as social controls. For the province-level regressions, we include the natural log of the GDP per capita and the ratio of employed persons to total province population as macro controls and the homicide rate, assault rate, and life quality score as social controls. The control variables are measured at a yearly frequency. For each control, we include the calendar year during which the recovery period started as well as two lags. The regression results are reported in Table 9: column 1 repeats the base results and columns 2 to 5 present the results when including only macro controls and including both macro and social controls, at respectively the regional and province level. The slight drop in observations in column (5) is explained by the fact that the crime rates data are not available for the Sardinian provinces as defined in the 2016 version of the NUTS classification. The estimated effects change very little when including the macro and social control variables, both in terms of magnitude and significance.

A.5 Province dummy interactions

The main specification includes dummies for the starting month and the length of the recovery period. The monthly dummies control for common time effects in the sample that could otherwise introduce spurious correlation between wildfire exposure and recovery rates. For instance, if wildfire activity increases over time and, for unrelated reasons, recovery rates on defaulted consumer credits also increase, not controlling for time effects could lead to an underestimation of the true impact of wildfire exposure on recovery rates. Controlling for common time effects using monthly (instead of yearly) dummies has the added advantage of eliminating seasonality in the data. This is especially relevant in the context of wildfires: between 2013 and 2019, about 75% of the total burned area in Italy was recorded in July and August.[14] This means that credits from the same province will on average have different levels of wildfire exposure (BA_{RP}) depending on the time of the year in which the recovery process takes place.[15] Hence, the monthly time effects avoid that any unrelated seasonality in the recovery rates biases the estimation. Similarly, two otherwise identical credits will on average have a different wildfire exposure depending on the length of the recovery period (i.e., the number of months included in BA_{RP}). By controlling for the length of the recovery period, we avoid that the negative association between recovery period length and recovery rate is spuriously attributed to BA_{RP}.

While the main specification includes sample-wide dummies, effectively controlling for common time effects, seasonality, and length of the recovery period at the national level,

[14] Source: authors' own calculations based on the EFFIS dataset used in this paper.

[15] This is not the case for the yearly measures (BA_{-1y} and BA_{-2y}) as they always include 12 months.

there may be heterogeneity within the country. For instance, different regions can experience different levels of economic growth, recovery rates may exhibit stronger seasonality in tourism-dependent areas, etc. We address these concerns by controlling for time effects, seasonality, and recovery period length, separately for each province instead of at the national level. In Table 10, we report the results from three regression models that include an interaction term between the province of the debtor (NUTS 3 level) and respectively (1) the starting year of the recovery period, (2) the starting month of the year (Jan-Dec) of the recovery period, and (3) the number of months included in the recovery period. These models also include all of the control and dummy variables from the main specification. The estimated effects of wildfire exposure during and before the recovery period differ little from the baseline results and remain highly significant.

A.6 Remove most frequent and largest exposure values

Given the unusual distribution of the wildfire exposure measures, with less than half of the observations having a value different from zero and and some notable outliers, we perform a few robustness checks to make sure that our results are not driven by a few anomalies. In column 2 of Table 11, we drop all observations with $BA_{RP} = 0.2065$, which is the most common value in the sample and is associated with credits acquired from the province of Naples in 2016. This constitutes 17,481 observations or 0.6% of the sample. In column 3, we drop all 13,125 observations (0.4% of the sample) with a value for $BA_{RP} \geq 4$, which corresponds to the top 3 largest wildfire exposures during the recovery period, all associated with credits from Naples. Given that many (large) wildfire exposures in our sample are associated with credits that originate from Naples, we perform a final robustness check (column 4) in which we remove the entire province from our sample. This drops about 12% of all observations. Comparing the results from the baseline model reported in column 1 to the these checks highlights that the estimated negative effect of wildfire exposure during the recovery period is highly robust to removing notable values of the BA measure and a large portion of the sample. The coefficients on the lag measures also remain highly significant, with the exception of the second lag in column 4.

B Tables

Table 1: Descriptive statistics - Defaulted consumer credits

Variable	μ	σ	P25	P50	P75
Total to Recover (EUR)	399.5	506.2	126.6	248.8	459.2
Principal (% TtR)	91.2	15.3	89.0	97.6	100.0
Debtor Age	49.1	13.5	39.0	48.0	58.0
Recovery Period (months)	3.8	2.0	2.0	4.0	5.0

This table presents descriptive statistics for the observed characteristics of the defaulted consumer credits. Columns μ and σ report the mean and standard deviation, respectively. Columns P25, P50, and P75 represent the 25th percentile, median, and 75th percentile values.

N = 3,049,627

Table 2: Descriptive statistics - Wildfire exposure measures

Variable	N	%	μ	σ	P25	P50	P75	Max
$\text{BA}_{RP} > 0$	659,073	22%	0.37	0.76	0.03	0.09	0.32	4.10
$\text{BA}_{-1y} > 0$	1,360,871	45%	0.53	0.89	0.04	0.21	0.58	4.10
$\text{BA}_{-2y} > 0$	1,287,119	42%	0.66	1.03	0.04	0.21	0.76	4.10

This table presents descriptive statistics for the wildfire exposure measures included in the regressions. Columns N and % show the number and proportion of observations with at least one recorded wildfire. The statistics reported in the next columns pertain to this subset of observations. Columns μ and σ report the mean and standard deviation, respectively. Columns P25, P50, and P75 represent the 25th percentile, median, and 75th percentile values, while the Max column indicates the highest recorded value.

Table 3: Results - Logistic regression

	(1) Coefficient	(2) Odds ratio	(3) OR (P10)	(4) OR (P50)	(5) OR (P90)
BA_{RP}	-0.110***	0.896	0.999	0.990	0.898
	(-6.11)				
BA_{-1y}	-0.066**	0.936	0.999	0.986	0.902
	(-3.14)				
BA_{-2y}	-0.066***	0.936	0.999	0.986	0.897
	(-4.22)				
ln(TtR)	-1.006***	0.366			
	(-24.69)				
Principal (% TtR)	0.029***	1.030			
	(28.20)				
Debtor Age	0.009***	1.010			
	(25.59)				
Observations	3,049,627				
Pseudo R^2	0.245				

This table presents the results of the baseline regression model detailed in Section 3.4. Column 1 reports logistic regression coefficients with t-statistics in parentheses. Column 2 reports the corresponding odds ratios, while columns 3 to 5 report the odds ratios at the 10th, 50th, and 90th percentile value of the BA variables with some wildfire exposure, respectively. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Results - BA median split

	(1)	(2)
$BA_{RP} \geq P50$	-0.111***	-0.104***
	(-6.26)	(-5.22)
$BA_{RP} < P50$		1.542
		(1.12)
$BA_{-1y} \geq P50$	-0.067***	-0.081***
	(-3.38)	(-3.95)
$BA_{-1y} < P50$		-0.292
		(-0.74)
$BA_{-2y} \geq P50$	-0.066***	-0.062***
	(-4.36)	(-3.72)
$BA_{-2y} < P50$		0.238
		(1.17)
ln(TtR)	-1.006***	-1.006***
	(-24.69)	(-24.74)
Principal (% TtR)	0.029***	0.029***
	(28.21)	(28.41)
Debtor Age	0.009***	0.009***
	(25.58)	(25.57)
Observations	3,049,627	3,049,627
Pseudo R^2	0.245	0.245

This table presents the results of the estimations detailed in Section 4.2. Columns report logistic regression coefficients with t-statistics in parentheses. In column 1, below-median wildfire exposures are censored to zero. Column 2 includes above-median and below-median wildfire exposures as separate variables. The median for each exposure variable is based on observations with some wildfire exposure ($BA > 0$). Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Results - Extensions

	(1)	(2)	(3)	(4)	(5)
BA_{RP}	-0.110***	-0.110***	-0.103***	-0.159***	-0.188***
	(-6.11)	(-6.13)	(-5.23)	(-5.04)	(-4.33)
BA_{-1y}	-0.066**	-0.067**	-0.047*	-0.122***	-0.169**
	(-3.14)	(-3.14)	(-2.53)	(-3.80)	(-2.72)
BA_{-2y}	-0.066***	-0.066***	-0.030	-0.080*	-0.114***
	(-4.22)	(-4.22)	(-0.72)	(-2.04)	(-3.46)
$BA_{RP} \times \%City_{RP}$				0.126*	
				(2.40)	
$BA_{-1y} \times \%City_{-1y}$				0.137*	
				(2.49)	
$BA_{-2y} \times \%City_{-2y}$				0.030	
				(0.33)	
$BA_{RP} \times \%ManMade_{RP}$					3.470*
					(2.25)
$BA_{-1y} \times \%ManMade_{-1y}$					4.330*
					(1.98)
$BA_{-2y} \times \%ManMade_{-2y}$					1.939
					(1.32)
Control variables	Yes	Yes	Yes	Yes	Yes
Dummies	Yes	Yes	Yes	Yes	Yes
Observations	3,049,627	3,049,627	3,049,627	3,049,627	3,049,627
Pseudo R^2	0.245	0.245	0.244	0.245	0.245

This table presents the results of the estimations detailed in Sections 3.2.1 and 3.2.2. Columns report logistic regression coefficients with t-statistics in parentheses. Columns 1 and 2 both represent the baseline model, estimated using the province-level BA measures and the LAU-based aggregated BA measures, respectively. In column 3, we use LAU-population-weighted wildfire exposures. Columns 4 and 5 include interaction terms between the wildfire exposure measures and the fraction of the burned area that occurred in city LAUs and man-made environments, respectively. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Results - Exclude last month from BA_{RP}

	(1)	(2)
BA_{RP}	-0.101***	
	(-4.90)	
BA_{RP-1m}		-0.105***
		(-5.63)
BA_{-1y}	-0.055*	-0.053*
	(-2.38)	(-2.34)
BA_{-2y}	-0.027	-0.025
	(-1.80)	(-1.68)
ln(TtR)	-1.035***	-1.035***
	(-26.39)	(-26.38)
Principal (% TtR)	0.028***	0.028***
	(29.54)	(29.57)
Debtor Age	0.009***	0.009***
	(25.28)	(25.28)
Observations	2,828,389	2,828,389
Pseudo R^2	0.222	0.222

This table presents the results of the estimations detailed in Appendix A.1. Columns report logistic regression coefficients with t-statistics in parentheses. Column 1 presents results from the baseline model estimated on the subset of credits with a recovery period of at least 2 months. In column 2, the same sample is used and BA_{RP} excludes the last month of the recovery period. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Results - No recent wildfires

	(1)
BA_{RP}	-0.604*
	(-2.41)
ln(TtR)	-0.985***
	(-38.54)
Principal (% TtR)	0.032***
	(22.93)
Debtor Age	0.010***
	(21.58)
Observations	1,333,444
Pseudo R^2	0.225

This table presents the results of the estimation detailed in Appendix A.2. Column 1 reports logistic regression coefficients, with t-statistics in parentheses, of the baseline model estimated on the subset of credits with no wildfire exposure in the two years preceding the start of the recovery period. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Results - Include credits with non-binary recovery rate

	(1)	(2)	(3)
BA_{RP}	-0.110***	-0.086***	-0.079***
	(-6.11)	(-6.84)	(-6.69)
BA_{-1y}	-0.066**	-0.056**	-0.046**
	(-3.14)	(-3.20)	(-3.02)
BA_{-2y}	-0.066***	-0.049**	-0.037**
	(-4.22)	(-3.27)	(-2.78)
ln(TtR)	-1.006***	-0.796***	-0.587***
	(-24.69)	(-28.47)	(-26.05)
Principal (% TtR)	0.029***	0.023***	0.015***
	(28.20)	(31.20)	(21.83)
Debtor Age	0.009***	0.009***	0.010***
	(25.59)	(28.45)	(26.88)
Observations	3,049,627	3,463,388	3,463,388
Pseudo R^2	0.245	0.168	0.140

This table presents the results of the estimations detailed in Appendix A.3. Columns report logistic regression coefficients with t-statistics in parentheses. Column 1 repeats the baseline results in which credits with a non-binary recovery rate are excluded from the estimation. In columns 2 and 3, non-binary recovery rates are converted to 0 or 1 and included in the estimations. In column 2, recovery rates greater than or equal to 0.50 are converted to 1. In column 3, all recovery rates greater than 0 are converted to 1. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Results - Macro and social control variables

	(1)	(2)	(3)	(4)	(5)
BA_{RP}	-0.110***	-0.109***	-0.105***	-0.111***	-0.112***
	(-6.11)	(-6.29)	(-7.04)	(-6.61)	(-7.69)
BA_{-1y}	-0.066**	-0.067***	-0.074***	-0.069**	-0.065***
	(-3.14)	(-3.46)	(-3.71)	(-3.20)	(-3.70)
BA_{-2y}	-0.066***	-0.061**	-0.059*	-0.062***	-0.060***
	(-4.22)	(-3.07)	(-2.55)	(-3.94)	(-3.61)
ln(TtR)	-1.006***	-1.006***	-1.007***	-1.007***	-1.009***
	(-24.69)	(-24.71)	(-25.10)	(-24.84)	(-24.65)
Principal (% TtR)	0.029***	0.029***	0.029***	0.029***	0.029***
	(28.20)	(28.73)	(29.29)	(28.82)	(28.71)
Debtor Age	0.009***	0.009***	0.009***	0.009***	0.010***
	(25.59)	(25.56)	(25.72)	(25.74)	(26.18)
Macro controls	No	Region	Region	Province	Province
Social controls	No	No	Region	No	Province
Observations	3,049,627	3,049,627	3,049,627	3,049,627	3,010,505
Pseudo R^2	0.245	0.245	0.245	0.245	0.246

This table presents the results of the estimations detailed in Appendix A.4. Columns report logistic regression coefficients with t-statistics in parentheses. Column 1 represents the baseline model that does not include macro-economic or social control variables. Columns 2 and 3 include macro-economic and social controls at the region (NUTS 2) level. Columns 4 and 5 include macro-economic and social controls at the province (NUTS 3) level. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Results - Province dummy interactions

	(1)	(2)	(3)
BA_{RP}	-0.131***	-0.123***	-0.108***
	(-11.64)	(-4.58)	(-5.65)
BA_{-1y}	-0.087***	-0.059**	-0.057***
	(-7.01)	(-3.26)	(-3.32)
BA_{-2y}	-0.066*	-0.070***	-0.070***
	(-2.44)	(-5.80)	(-5.36)
ln(TtR)	-1.009***	-1.007***	-1.002***
	(-25.36)	(-24.65)	(-24.61)
Principal (% TtR)	0.029***	0.029***	0.029***
	(30.09)	(30.46)	(28.53)
Debtor Age	0.010***	0.010***	0.010***
	(26.94)	(27.72)	(26.54)
NUTS 3 ×	Year	MoY	RP (months)
Observations	3,049,627	3,049,627	3,048,815
Pseudo R^2	0.247	0.251	0.247

This table presents the results of the estimations detailed in Appendix A.5. Columns report logistic regression coefficients with t-statistics in parentheses. Column 1 includes province-year dummies. Column 2 includes province-month-of-year dummies. Column 3 includes province-recovery-period-length dummies. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Results - Remove most frequent and largest exposure values

	(1)	(2)	(3)	(4)
BA_{RP}	-0.110***	-0.111***	-0.108***	-0.145***
	(-6.11)	(-6.19)	(-3.88)	(-5.57)
BA_{-1y}	-0.066**	-0.068**	-0.066**	-0.113***
	(-3.14)	(-3.27)	(-3.13)	(-4.36)
BA_{-2y}	-0.066***	-0.068***	-0.066***	-0.057
	(-4.22)	(-4.34)	(-4.22)	(-1.47)
ln(TtR)	-1.006***	-1.005***	-1.005***	-0.978***
	(-24.69)	(-25.19)	(-24.88)	(-30.45)
Principal (% TtR)	0.029***	0.029***	0.029***	0.030***
	(28.20)	(28.37)	(26.51)	(28.69)
Debtor Age	0.009***	0.009***	0.009***	0.009***
	(25.59)	(25.39)	(26.05)	(24.64)
Observations	3,049,627	3,032,146	3,036,502	2,693,714
Pseudo R^2	0.245	0.245	0.245	0.233

This table presents the results of the estimations detailed in Appendix A.6. Columns report logistic regression coefficients with t-statistics in parentheses. Column 1 presents the baseline results for comparison. Column 2 excludes observations with the most frequent value of BA_{RP}, column 3 excludes the largest exposures ($BA_{RP} \geq 4$) from the estimation, and column 4 excludes all credits from Naples. Standard errors are clustered at province level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C Figures

Figure 1: Distribution of realized recovery rates of defaulted consumer credits