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The regional economic impact of wildfires: Evidence from Southern Europe[☆]

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ABSTRACT

We estimate the impact of wildfires on the growth rate of gross domestic product (GDP) and employment of regional economies in Southern Europe from 2011 to 2018. To this end we match Eurostat economic data with geospatial burned area perimeters based on satellite imagery for 233 Nomenclature of Territorial Units for Statistics (NUTS) 3 level regions in Portugal, Spain, Italy, and Greece. Our panel fixed effects instrumental variable estimation results suggest an average contemporary decrease in a region's annual GDP growth rate of 0.11–0.18% conditional on having experienced at least one wildfire. For an average wildfire season this leads to a yearly production loss of 13–21 billion euros for Southern Europe. The impact on the employment growth rate is heterogeneous across economic activity types in that there is a decrease in the average annual employment growth rate for activities related to retail and tourism (e.g., transport, accommodation, food service activities) of 0.09–0.15%, offset by employment growth in insurance, real estate, administrative, and support service related activities of 0.13–0.22%.

1. Introduction

In recent years news coverage of orange coloured skies, evacuations, and devastation caused by wildfires has become all too familiar. Even though one tends to only hear about the most calamitous and tragic of fires, every summer Southern European countries experience a large number of fires of varying degrees of seriousness (San-Miguel-Ayanz et al., 2021, 2022). These events can be highly disruptive and destructive, affecting different sectors of the economy, such as forestry and agriculture (Butry et al., 2001; Rego et al., 2013), industry and construction (Kramer et al., 2021; Wang et al., 2021), and recreation and tourism (Kim and Jakus, 2019; Molina et al., 2019; Gellman et al., 2022; Otrachshenko and Nunes, 2022). Importantly, natural disasters, including wildfires, are for the most part localised events that are likely to induce predominantly local effects that could potentially be disguised if one only considers aggregated data at the national level (Horwich, 2000).[1] Given increasing European regional inequality particularly in Southern Europe (Iammarino et al., 2019) and the possibility that the region faces an increased risk of wildfires due to climate change (Dupuy et al., 2020; Sullivan et al., 2022), being able to identify and quantify the potential economic impact of

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[1] Wildfires may also have more wide reaching effects through drifting smoke pollution although this aspect is not specifically considered in this study.

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wildfires has important implications for regional policy making. In this paper we explicitly set out to examine the regional gross domestic product (GDP) and employment impacts of wildfires in Southern Europe since 2010.

There is now a sizeable theoretical and empirical literature focusing on the impacts of natural disasters other than wildfires on GDP growth. For example, negative effects are found after hurricanes (Strobl, 2011), cyclones (Naguib et al., 2022), and floods (Parida et al., 2021). Furthermore, Barone and Mocetti (2014) show a short-term negative effect on GDP growth from a study of two earthquakes in Italy, but report a positive long-term effect for one of them. While a majority of studies do report predominantly negative effects, the literature does not offer conclusive evidence and impacts depend on a variety of dimensions, such as on severity, disaster type, and country of occurrence (Loayza et al., 2012; Fomby et al., 2013). Nevertheless, conducting a meta-analysis using more than 750 estimates from publications studying the relationship between natural disasters, Klomp and Valckx (2014) conclude that there is a genuine negative effect that is increasing over time. Similarly, Felbermayr and Gröschl (2014) construct a comprehensive disaster data set from geophysical and meteorological information as opposed to using insurance data, and also find a robust negative effect of natural disasters on GDP growth.

A number of studies have also examined the employment impact of natural disasters, although the evidence is scarcer and much more mixed. As Deryugina (2022) notes, natural disasters can affect the labour market equilibrium through a number of different channels. For example, if areas that heavily rely on tourism are impacted, employment in the hospitality sector is likely to fall. For example, Barattieri et al. (2021) show short-term negative employment and wage impacts for hurricane affected counties in Puerto Rico between 1995 and 2017. Similarly, Deryugina et al. (2018) show a short-run decline in labour market outcomes following hurricane Katrina. However, labour demand in other sectors could arguably increase through an element of "creative destruction", whereby damaged sub-optimal infrastructure is replaced with superior technology in the rebuilding phase. In this regard, Groen et al. (2020) find an increase in regional employment for those industries that are reconstruction related following hurricanes Katrina and Rita in 2005.

While assessing the economic impact of wildfires from a general natural hazards perspective can provide considerable insights, as pointed out by McCaffrey (2004), wildfires are also characterised by features that make them unique compared to other natural disasters. For instance, wildfires can perform beneficial functions for ecosystems under certain scenarios (Holmes et al., 2008). Moreover, wildfires are often human induced in that socioeconomic factors, such as poverty, education, or illegal activity, can contribute to the probability of wildfire occurrence (Michetti and Pinar, 2019), resulting in potential damage that is more easily mitigated or exacerbated by policy measures (e.g., land management, fire prevention) compared to other environmental hazards (Borgschulte et al., 2020).

Importantly, wildfires are particularly atypical among natural hazards since property damage can oftentimes be substantially reduced if there is large investment in manpower and equipment as described in Baylis and Boomhower (2019). Hence, central to understanding the potential economic impact of wildfires is the response during the hazard event itself. More specifically, during relatively short-duration hazards (e.g., earthquakes, hurricanes, floods) the mitigating response choice set for the direct effects is limited temporally, while wildfires can be actively "fought" and often last for several days or even weeks. Hence, an abundance of resources, including direct suppression spending and contracted services, are often made available during the wildfire event (Davis et al., 2014). If a substantial part of the employed services and goods are provided locally, these measures can also have major indirect impacts on regional economies. From an econometric perspective these aspects that are peculiar to wildfires raise important endogeneity concerns when trying to causally identify the economic impact of wildfires compared to other environmental disaster settings.

While a considerable body of literature has studied the conceivably detrimental and immediate impact of wildfires (Morton et al., 2003; Stephenson et al., 2013; CCST, 2020), a small number of studies scrutinise their effect on traditional economic indicators, such as GDP and employment growth. The most relevant research in this area was conducted by Nielsen-Pincus et al. (2013) who examine large wildfire events in the Western United States (US) and find an increase in county-level employment growth of 1% during the quarters where fire suppression efforts took place, although the effect is heterogeneous with regard to county characteristics and economic sectors (Nielsen-Pincus et al., 2014). Furthermore, Borgschulte et al. (2020) report reduced earnings of approximately 0.04% over two years per additional smoke exposure day for the US.

Although the impact of wildfires on the labour market or on GDP growth has to date drawn little attention, two other research areas evaluating economic impacts of wildfires are better understood. On the one hand, the hedonic pricing literature demonstrates a predominantly negative effect on house prices of up to 20% following wildfires in the US (Nicholls, 2019). Furthermore, Mueller and Loomis (2014) document that although property values are negatively affected by wildfires, there is large variation across the distribution of house prices, while McCoy and Walsh (2018) find a short-lived negative effect on property values if a burn scar can be viewed from the house. On the other hand, negative economic effects related to fire induced smoke pollution suggest that there are substantial health costs as demonstrated by Kochi et al. (2012), Richardson et al. (2012), Burke et al. (2020), Johnston et al. (2021), and Tarín-Carrasco et al. (2021). However, even for these relatively well researched aspects of wildfires, the majority of studies focus on the US and Australia, and not on Europe.

The current study makes three main contributions to the literature. First, we examine the economic implications of wildfires on regional employment and GDP growth in Europe, which to the best of our knowledge has not been explored. Since wildfires in Europe are perceived as a growing risk that predominantly affects Southern Europe, our study provides some of the first evidence on economic impacts for this fire-prone geographical region. Second, we focus on small-scale regional effects, which Horwich (2000) argues are important because natural disasters are for the most part localised events, and potential impacts are often imperceptible when studied at more aggregated geopolitical levels. As a matter of fact, neglecting potential regional economic impacts has already been identified as a major shortcoming of most previous studies addressing the impacts of natural hazards (Botzen et al., 2019).

Table 1
Sample composition and descriptive statistics showing the size of NUTS 3 regions by country.

	N	Proportion (%)	Mean (km^2)	sd (km^2)	Median (km^2)
Portugal	23	10	3,860	1,948	3,345
Spain	52	22	9,588	5,251	9,317
Italy	106	46	2,774	1,679	2,454
Greece	52	22	2,534	1,706	2,339

Notes: (i) Proportion (%) = the number of regions per country as a share of all sample regions; (ii) sd = standard deviation.

Third, in order to overcome potential endogeneity concerns when empirically estimating the economic effect of wildfires, we employ a novel causal identification strategy creating an instrumental variable (IV) by isolating climatic features for predominantly forested areas that are particularly relevant for capturing the probability of wildfire occurrence while also controlling for general and related climate conditions that might affect regional economic outcomes directly.

The empirical analysis in this paper relies on the construction of a panel data set matching annual regional economic data on employment and GDP growth from 2010 to 2018 with burned area (BA) polygons based on satellite imagery for regions in Portugal, Spain, Italy, and Greece. These data are combined with general climatic data, land cover maps, and a time-varying Fire Weather Index (FWI). Employing two-stage least squares (2SLS) instrumental variables regressions arguably allows us to causally quantify any potential effects of wildfires on annual regional employment and GDP growth in Southern Europe over our sample period.

To briefly summarise our results, we find an annual decrease in the rate of GDP growth of 0.11–0.18% for wildfire affected regions. Given that 102 regions are affected by wildfires every year on average, our findings indicate rough annual economic losses for Southern Europe in the range of 13–21 billion euros. There is also a heterogeneous impact on employment growth across economic activities where annual employment growth in tourism-related activities (e.g., accommodation, transportation, food service) decreases by 0.09–0.15%, while the sectors that include financial, insurance, real estate, and administrative activities experiences an average increase in the employment growth rate of 0.13–0.22%.

The remainder of the paper is organised as follows. Section 2 describes the data sources, how we constructed variables, and provides some descriptive statistics. Section 3 describes our identification strategy, the instrument construction, and econometric specification. Finally, the results are presented and discussed in Section 4 while Section 5 concludes.

2. Data and descriptive statistics

2.1. Regional unit of analysis and sample composition

The Nomenclature of Territorial Units for Statistics (NUTS) classification provides harmonised regional statistics for the European Union member and partner states. The hierarchical system divides the economic territory into major socio-economic regions (NUTS 1), basic regions for the application of regional policies (NUTS 2), and small regions for specific diagnoses (NUTS 3). Our countries of interest include a total of 243 NUTS 3 regions, namely 25 *Entidades Intermunicipais* for Portugal, 59 *Provincias* for Spain, 107 *Provincie* for Italy, and 52 *Omades Periferiakon Enotition* for Greece (Eurostat, 2020). For data availability and comparability reasons the following regions are excluded from our analysis: The Azores and Madeira for Portugal (2 regions), the Canary Islands for Spain (7 regions), and Sud Sardegna for Italy (1 region) leaving 233 NUTS 3 regions that are used in our analysis.[2]

Table 1 shows the sample composition and the disaggregated mean and median size of the NUTS 3 regions by countries. Italy accounts for almost half of the regions (46%), Spain and Greece each add up to about one fifth, and one in ten regions is in Portugal. One can observe variation in the mean size of a unit per country, with the largest regions in Spain, and the smallest in Italy and Greece, on average.

2.2. Economic data

We use data on regional level employment and per capita GDP as provided by the regional economic accounts of the Statistical Office of the European Union (Eurostat).[3] Regional accounts are derived from the corresponding national accounts, and thus, are generally defined using the concepts applied to national accounting procedures.[4] The estimation of regional GDP can follow either the production or the income approach.[5] The production approach measures regional GDP as the sum of gross value added (GVA), which is defined as the difference between output and intermediate consumption, plus taxes minus product subsidies. For the income

[2] The omissions for Portugal and Spain are due to missing meteorological and Fire Weather Index data, and the excluded Italian region is due to rearranged regional boundaries during the study period.

[3] https://ec.europa.eu/eurostat/web/rural-development/data (accessed in August 2021).

[4] It is noteworthy that a series of conceptual and practical difficulties arise when breaking down national data or compiling regional data directly. Challenges in accurate regional estimations involve how to account for enterprises with several regional establishments, extra-regio territory, major construction projects, cross regional boundary pipelines and cable distribution networks, or commuter flows, to name a few. For a detailed discussion with accompanying guidelines, see Chapter 13 in Eurostat (2013a) and Eurostat (2013b).

[5] Unlike for national data, the expenditure method cannot be applied given the absence of data on imports and exports on the regional level.

Table 2
Statistical classification of economic activities in the European community (NACE).

Category	Section	Description
A	A	Agriculture, forestry and fishing
B–E	B	Mining and quarrying
	C	Manufacturing
	D	Electricity, gas, steam and air conditioning supply
	E	Water supply, sewerage, waste management and remediation activities
F	F	Construction
G–J	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
	H	Transportation and storage
	I	Accommodation and food service activities
	J	Information and communication
K–N	K	Financial and insurance activities
	L	Real estate activities
	M	Professional, scientific and technical activities
	N	Administrative and support service activities
O–U	O	Public administration and defence; compulsory social security
	P	Education
	Q	Human health and social work activities
	R	Arts, entertainment and recreation
	S	Other service activities
	T	Activities of households as employers
	U	Activities of extraterritorial organisations and bodies

approach, regional GDP at basic prices is derived from measuring and aggregating the regional generation of income of the economy, i.e., wages and salaries, the sum of other taxes minus subsidies on production, employers' social contributions, gross operating surplus, and consumption of fixed capital. In practice, gross operating surplus is generally not available by region and industry which poses a barrier to using the income approach. In general, countries are free to choose their preferred estimation approach. Hence per capita figures can be calculated for all regions excluding extra-regio measures (Eurostat, 2013b).

Our measure of regional employment is from the European Union Labour Force Survey that is based on a household sample survey of people aged 15 years and over. Persons are categorised as "employed" if any work has been performed during the survey reference week (e.g., for pay or family gain) or if they had a job at the time but were temporarily absent due to illness, holidays or educational training. The aggregated annual average of employed persons makes allowance for the fact that some people are not employed over the entire year but do casual or seasonal work (Eurostat, 2013b). Using the population data provided by Eurostat we calculate the share of employed persons in the total population.[6] We are also able to disaggregate employment growth by sections based on the Statistical classification of economic activities in the European Community (NACE) Rev.2, which is a revised classification implemented in 2007.[7] More specifically, we use Eurostat data for six categories that combine and classify a total of 21 individual economic activity sections as shown in Table 2 (Eurostat, 2008).

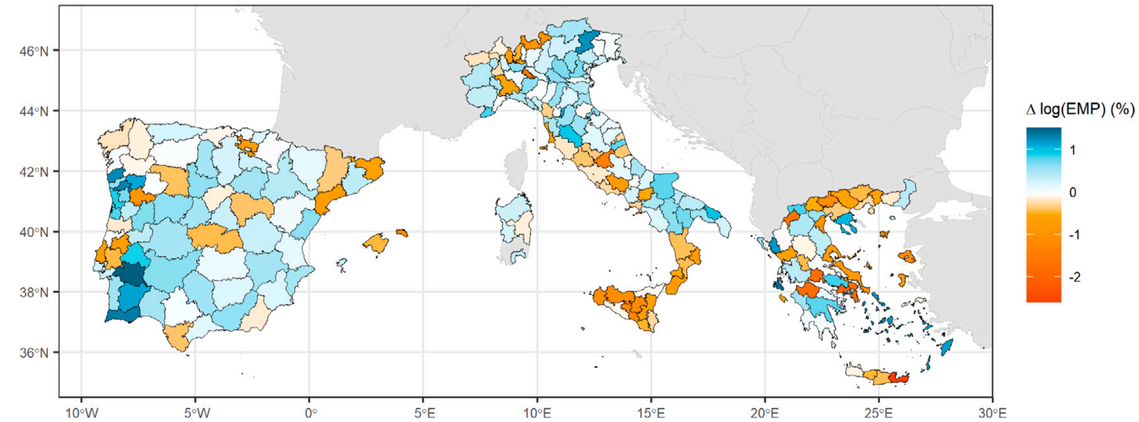
The regional economic variables are available from 2010 to 2018 and we use first differences of their logged values (i.e., growth rates) in our analysis. The geographical distribution of the average yearly employment and GDP growth rates across the NUTS 3 regions is shown in Fig. 1. The maps demonstrate that while the distribution of the employment growth rate (Fig. 1(a)) is fairly heterogeneous across countries, with intra-country regions experiencing both positive and negative employment growth rates over the study period, the emerging image for the GDP growth rates is strikingly different (Fig. 1(b)). Rather we observe clear differences at the country-level, indicating predominantly positive GDP growth in Portugal, Spain, and Italy, and negative growth in Greece.[8]

Descriptive statistics for the economic variables are summarised in Table 3. On average, 39.6% of the population is employed, and the employment growth rate is centred around zero with a slight tendency towards being positive. The smallest and largest values are within five standard deviations of the mean. The average per capita GDP is 21,184 euros, and on average positive GDP growth rates over the time period are observed. The GDP growth rates are within around six standard deviations of the mean.

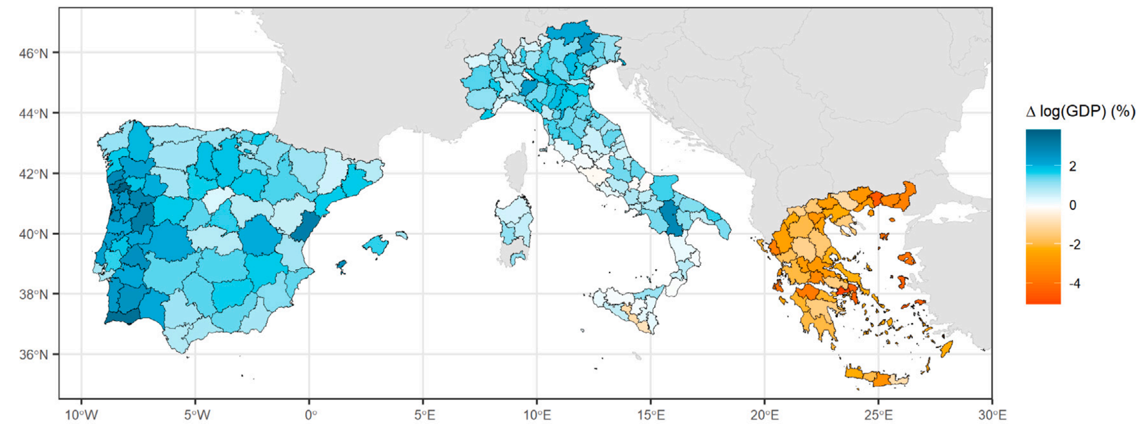
2.3. *Wildfire impact variables*

The impact of wildfires is proxied by fire numbers as an absolute measure, and BA as a share of a region's total area. The primary data set for the construction of these variables is the high-resolution harmonised spatial BA data product provided by the European Forest Fire Information System (EFFIS).[9] This data product is based on a semi-automatic approach that combines Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery with two bands (red and near-infrared) at a 250 meter spatial

[6] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10r_3popgdp&lang=en (accessed in August 2021).
[7] Derived from French, NACE translates as Nomenclature statistique des activités économiques dans la Communauté européenne.
[8] Note, that our study period starts shortly after the financial crisis where Greece was particularly hard hit.
[9] https://effis.jrc.ec.europa.eu (accessed in July 2021).



(a) Employment Growth



(b) GDP Growth

Fig. 1. Average annual employment and GDP growth rates (2011–2018).
Notes: (i) economic data are from the Statistical Office of the European Union (Eurostat); (ii) Δlog(EMP) denotes the growth of the employment rate and Δlog(GDP) is the per capita GDP growth rate.

Table 3
Descriptive statistics of economic variables (2010–2018).

	Min	Mean	sd	Median	Max	N
Employed/total population (%)	24.6	39.6	6.3	39.7	67.6	2,097
Δlog(EMP) (%)	−12.3	0.0	2.6	0.3	12.8	1,864
GDP/capita (€)	9,500	21,184	7,268	19,600	55,900	2,097
Δlog(GDP) (%)	−20.0	0.4	3.8	1.0	22.5	1,864

Notes: (i) economic data are from the Statistical Office of the European Union (Eurostat); (ii) Δlog(EMP) denotes the growth of the employment rate and Δlog(GDP) is the per capita GDP growth rate; (iii) sd = standard deviation.

resolution,[10] ancillary spatial data sets, and refinement of the perimeters through visual inspection backed up by news coverage. The burn perimeters are updated up to two times a day capturing fires larger than around 30 hectares.[11] In order to analyse potential lagged effects on the economic outcome variables our study includes all fires from 2001 to 2018.

[10] There are five bands (blue, green, as well as three short-wave infrared bands) with spatial resolution of 500 meters that help to improve BA discrimination by providing complementary information.

[11] https://effis.jrc.ec.europa.eu/about-effis/technical-background/rapid-damage-assessment (accessed in July 2021).

Table 4
Descriptive statistics of wildfire impact variables and the Fire Weather Index (2010–2018).

	Min	Mean	sd	Median	Max	N
All observations						
FIRE	0	3	9	0	129	2,097
BA (%)	0	0.34	1.53	0	33.82	2,097
Wildfire affected observations						
FIRE	1	7	13	2	129	920
BA (%)	0.001	0.77	2.24	0.13	33.82	920
Instrument						
FWI forest	0.0	15.9	11.6	14.9	64.8	2,097

Notes: (i) FIRE indicates the annual number of wildfires per region; BA in % denotes the annual burned area relative to the total area per region; FWI forest indicates the daily mean Fire Weather Index over the summer months for predominantly forested areas; (ii) "Wildfire affected observations" includes all observations where at least one wildfire occurred in a given year; (iii) sd = standard deviation.

For cross-border wildfires that affect several regions, the burn perimeters are split according to the NUTS 3 regional boundaries.[12] We exclude all fires that burned less than five hectares after the splitting process from the fire count variable, while all burned area counts towards the BA variable. Between 2010 and 2018 the number of wildfires in the dataset is 6709, whereby less than 1% resulted from the splitting process by regions. The total area burned over this period is approximately 2.4 million hectares.

The wildfire impact proxy variables are summarised in Table 4 for 2010 to 2018.[13] The mean fire number for all regions is three, and an annual average of 0.3% of a region is burned. Only considering the observations that experienced at least one fire denoted as "wildfire affected observations", the mean fire number is seven with an average of approximately 0.8% of total area burned. In our sample, one or more wildfires occurred in about 44% of the observations, and 82% of the regions were affected over the study period. On average about a third of the regions (30%) experience a wildfire each year.

Regarding the spatial distribution of the average annual wildfire numbers shown in Fig. 2(a), most fires are observed in Southern Italy and in the Northwest of the Iberian Peninsula. Focusing on the BA (proportional to the total area of a region) displayed in Fig. 2(b), the highest values are in Central and Northern Portugal. Fig. 2(c) shows the average wildfire size in hectares for each region over the study period. In contrast to Fig. 2(a) and Fig. 2(b), there are comparably low values for Italy and large values for the average fire size in Greece.

2.4. *Fire weather index (FWI)*

The FWI is a component of the Canadian Forest Fire Weather Index System initially introduced by Van Wagner and Pickett (1985). Fig. 3 presents a schematic of the FWI structure. The FWI captures relative fire potential, and serves as primary reference index to the Joint Research Centre (the European Commission's science and knowledge service) in the production of fire danger maps (Camia et al., 2008). The FWI is based on the combination of the two fire behaviour indices (1) Initial Spread Index (ISI) and (2) Buildup Index (BUI). The ISI estimates fire spread potential by integrating the Fine Fuel Moisture Code (FFMC), which is intended to represent fuel moisture conditions for litter fuels shaded by the forest canopy, and surface wind speed (u and v components).[14] The BUI provides information on potential heat release incorporating fuel moisture information from deeper soil layers. More specifically, it combines the Duff Moisture Code (DMC) capturing decomposed organic material below the litter fuels, and the Drought Code (DC) representing the moisture content of the deep compact layer assessing seasonal drought effects on heavy fuels. Both the DMC and the DC are adjusted for day-length of the month.

As can be seen from Fig. 3, the basic climatic inputs underlying the construction of the FWI are temperature, relative humidity, wind speed, and precipitation. All variables are measured at solar noon standard time. Precipitation is an accumulated measure over 24 h. The details of the construction from the initial meteorological observations to the derivation of the fire behaviour indices ISI and BUI are beyond the scope of this paper, but are described in Van Wagner and Pickett (1985). However, we do provide an outline of the calculations for the fire behaviour indices for the FWI in Appendix A.

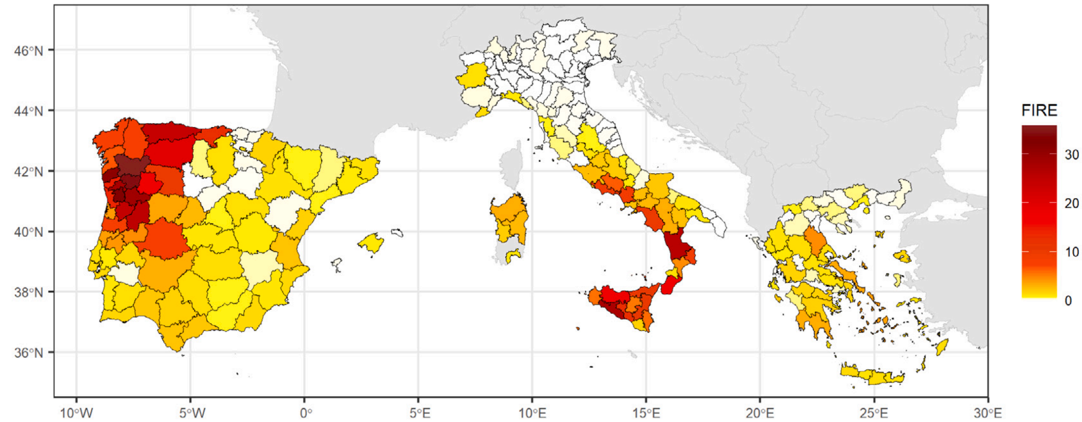
We use the daily FWI calculated by Natural Resources Canada presented in McElhinny et al. (2020). The primary meteorological inputs are from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 HRES reanalysis product with a spatial resolution of 0.25° (approximately 27–28 kilometres in our latitudes of interest).[15] We work with the FWI version using the overwintered DC, which captures inter-seasonal drought. This is preferable to using a default start value as the overwintered DC is more precise accounting for precipitation in the winter months.

[12] The NUTS 2016 version of the shapefile scaled 1:1 million is provided by Eurostat at https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts is used (accessed in July 2021).

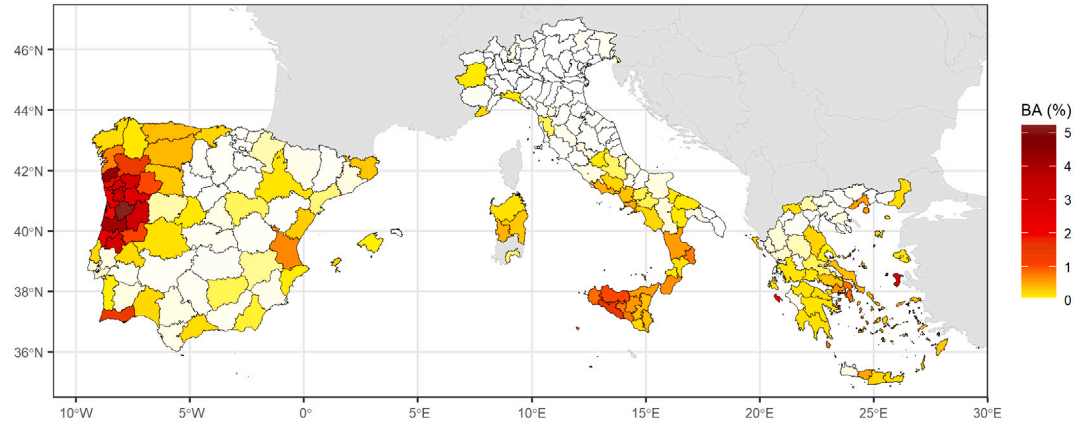
[13] Although we have data from 2001 to 2018 we display the descriptive statistics for the period that matches the economic outcome variables since these figures are later used to interpret the regression coefficients.

[14] u is the component of the horizontal wind towards east (zonal velocity) and v denotes its counterpart towards north (meridional velocity).

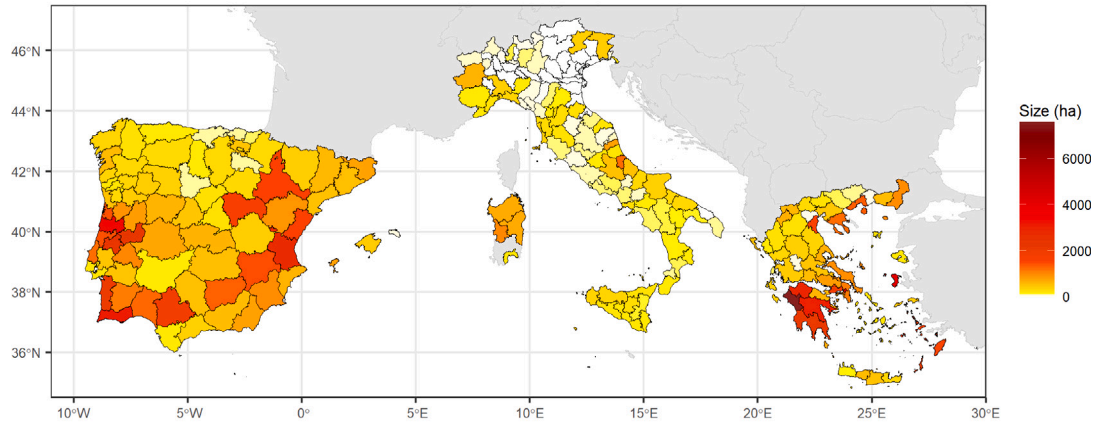
[15] Note, the primary resolution of ERA5 is 0.28125° on a reduced Gaussian grid, but the output on a regular geographical grid is 0.25°.



(a) Fire Number



(b) Proportion Burned



(c) Average Fire Size

Fig. 2. Average annual wildfire occurrence (2010–2018).

Notes: (i) wildfire data is taken from a high-resolution burned area product provided by the European Forest Fire Information System (EFFIS); (ii) FIRE indicates the annual number of wildfires per region; BA in % denotes the annual burned area relative to the total area per region; Size indicates the average size of a fire in hectares (ha).

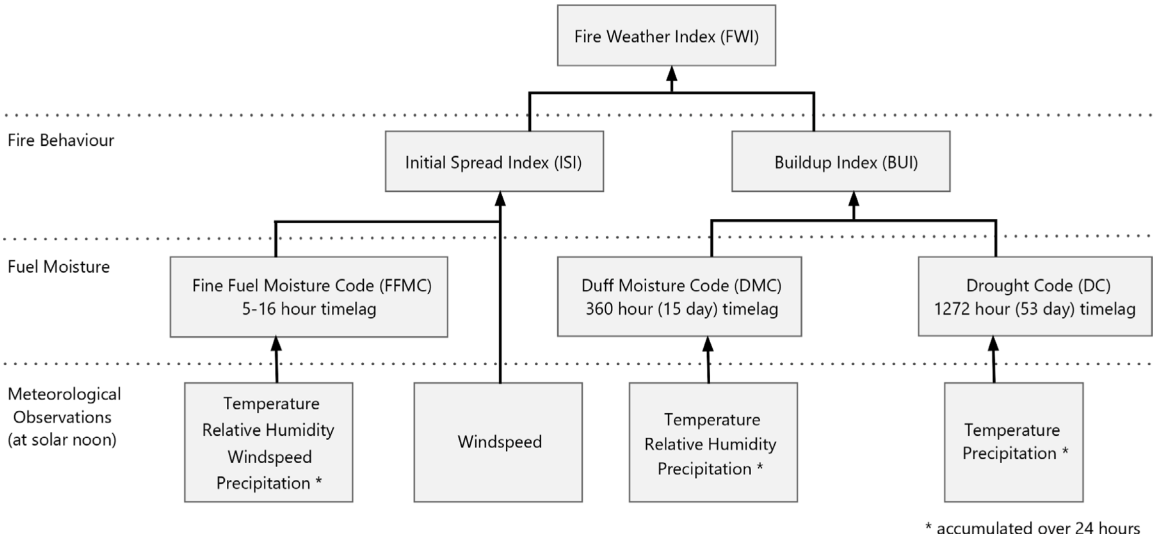


Fig. 3. Structure of the Canadian Fire Weather Index System based on Van Wagner and Pickett (1985).

2.5. Land cover data

We resort to the CORINE land cover (CLC) data provided by the Copernicus Land Monitoring Service in order to distinguish between forested and non-forested areas within the studied regions.[16] CLC is specified to standardise land cover data collection in order to support environmental policy development. It was initialised in 1990 and is updated every six years. While orthocorrected satellite images provide the basis for the land cover mapping, ancillary information such as in-situ and ground survey data enhance accuracy.[17] The minimum mapping unit/width is 100 m (25 hectares) with a thematic accuracy exceeding 85%. The CLC inventory comprises 44 land cover types (European Environment Agency, 2021).

We use the raster files of the years 2006 and 2012 and reclassify the 44 land cover types into four suitable categories for our study purposes, namely urban areas (i.e., artificial surfaces), agricultural areas, forested areas (including forests as well as shrub and/or herbaceous vegetation), as well as wetlands and water bodies (also including open spaces with little or no vegetation). See Table B1 in Appendix B for the exact reclassification.

2.6. Climatological data

Temperature, precipitation, and relative humidity data are taken from the E-OBS, a daily gridded meteorological data set for Europe with a spatial resolution of 0.25° and is derived from in-situ observations based on the station network of the European Climate Assessment & Dataset (ECA&D) project.[18] Temperature is measured in degrees Celsius at a height of two metres and daily precipitation consists of the total amount of rain, snow, or hail (equivalent to the height in liquid water per square meter) in millimetres. Daily averaged relative humidity in percentage is based on the observational station time series from ECA&D. In order to remove data skewness, the relative humidity values are transformed by $\sqrt{100 - relative\ humidity}$ before the fitting process to ensure all interpolated values are equal or smaller than 100 when converted to percentages.

For every NUTS 3 region, we take the following approach to calculate seasonal and annual average temperature, precipitation, and relative humidity for each of the four land cover type categories (i.e., urban, agriculture, forest, wetland and water bodies). First, an E-OBS gridcell for a specific land cover type is matched with a region if, in the overlapping part of the region and the E-OBS gridcell, a majority of the area is of that specific land cover type. Second, we average all the E-OBS gridcell values that are matched for a specific region and land cover type. Third, we use the daily meteorological data to calculate seasonal, i.e., summer months, and annual average temperature, precipitation and relative humidity for each of the four land cover types.

Even though the E-OBS data set provides information on wind speed, there are many missing values, particularly for Southern Greece and Sicily. Therefore, we instead use the 10 meter u and v wind components from the fifth generation of the ECMWF atmospheric reanalyses of the global climate (ERA5) data product (Hersbach et al., 2020). The spatial resolution of 0.25° is similar to the E-OBS data set and the temporal resolution is hourly. We extract daily values at 12 pm and match the ERA5 gridcells with

[16] https://land.copernicus.eu/pan-european/corine-land-cover (accessed in August 2022).

[17] Both the 2006 and the 2012 versions are based on the Indian Remote-Sensing Satellite P6 LISS III and on the dual date satellites (Sentinel-2 and Landsat 8). SPOT-4/5 is additionally used for year 2006 and RapidEye Earth-imaging Systems for year 2012.

[18] For details see Cornes et al. (2018).

the NUTS 3 regions for each land cover type in a similar manner as described for the other climatic variables. Once processed to seasonal and annual average values, wind speed is calculated from the u and v component where $wind\ speed = \sqrt{u^2 + v^2}$.

3. Empirical framework

3.1. Identification strategy

The identification of the causal effect of wildfires on regional economies is complicated by the potential endogeneity of the wildfire proxy impact variables. As we employ geophysical measures, i.e., remotely sensed imagery defining the BA, in conjunction with regional level fixed effects, the source of endogeneity typically induced by using reported loss or damage data (e.g., through insurance claims that are likely to correlate with GDP/capita) is avoided, as outlined in Felbermayr and Gröschl (2014). However, using ordinary least squares (OLS) with regional level fixed effects, even with the geophysical based measures of the fires, might still produce biased estimates due to a number of time varying unobserved factors. Regional unobservables include, inter alia, fire and land management policies (e.g., fire prevention and suppression regimes), rural exodus/urbanisation rates, land-use changes (e.g., deforestation), land-use regulations, political instability, and local government corruption. These endogeneity concerns are particularly important for wildfires as opposed to other natural disasters because wildfires are often due to human induced activities (under the right climatic conditions) and are generally not instantaneous events.

The likely direction of bias for the aforementioned factors will differ depending on which unobservable one is considering. If the unobservable is negatively correlated with wildfire occurrence and positively correlated with the economic outcome variables or vice versa, we expect a downward bias of the OLS estimate. For example, one might expect wildfires to be reduced if a region implements effective fire prevention measures (e.g., mechanical clearing of land, fire breaks, grazing, educational campaigns), but at the same time employment may be increased as workers are needed to carry out these interventions. Likewise, urbanisation may coincide with a larger demand for fire services, which may also increase employment and hence reduce the BA as there are more locally available suppression resources. Turning to land-use changes, if the change is from forested to agricultural land (deforestation), this is likely to increase economic activity as it might be a more profitable use of land and would also decrease wildfires which generally occur in forested areas. A downward bias would also be observed for the case of political instability or corruption levels that lead to a potential increase in BA, e.g., around elections (Skouras and Christodoulakis, 2014) which could at the same time plausibly have a negative impact on economic activity.

One might also expect upward biased estimates if certain unobservables are taken into account that are positively correlated with both wildfire occurrence and employment/output. For example, a rural exodus would result in abandoned and unmanaged forests which potentially increases wildfire occurrence, but could also increase GDP growth if there are better job opportunities in regional economic centres. Furthermore, certain environmental regulations might create perverse incentives for arson (e.g., if the burned land can subsequently be used for cultivation or construction) so that the fire numbers potentially increase, quite possibly accompanied by the creation of employment and GDP growth if the land is repurposed towards more productive activities.

Finally, OLS estimates may suffer from classical measurement error, which leads to a bias towards zero introduced by measuring the BA using satellite data that is arguably imperfect. More specifically, the data is based on a multi-step process, which means that the data is heavily reliant on working instruments on board the satellites at all times, but also on visual inspection and manual processing. Both aspects could thus lead to attenuation bias. Moreover, as described in Alix-Garcia and Millimet (2021) and Garcia and Heilmayr (2022) using satellite data can induce non-classical (systematic) measurement error. More specifically, as noted in Section 2.3, not all fires smaller than 30 hectares are detected by the satellite. Therefore, the true BA might be marginally larger than in our data set. While Alix-Garcia and Millimet (2021) provide a solution if the data derived by remotely sensed imagery is used as the dependent variable in a regression, we are not aware of an applicable strategy if the independent variable is based on satellite data, as it is in our case. This thus constitutes a limitation of our study.

Our empirical strategy is to isolate time-varying fire danger for the predominantly forested areas in the summer months which is arguably a good predictor for wildfire occurrence (first stage). As described in Section 2.4, the FWI is based on meteorological inputs and can thus be considered as good as randomly assigned. Moreover, by construction the FWI arguably only picks up the distinctive part of the meteorological factors indicative of wildfire danger. In order to ensure the satisfaction of the exclusion restriction we implement two vectors of control variables. First, we also include the FWI in predominantly urban, agricultural, and wetlands and water body areas of a region. Second, we control for a battery of other climatic variables i.e., temperature, precipitation, relative humidity and wind speed within the region. Every climatic variable is created separately for each of the four land cover types and is included both as summer month averages and as annual averages. By including these additional control factors we are thus ensuring that our instrument is not capturing climatic factors affecting the non-predominantly-forested areas within a region that might affect economic activity other than through wildfire occurrence, such as, for example, through their impact on the agricultural sector (Damania et al., 2020).

Since the inputs into the FWI are also temperature, precipitation, relative humidity and wind speed, the FWI captures the remaining variation through the joint occurrence of specific threshold values and/or their non-linear transformations of these in its construction.[19] Moreover, some inputs into the FWI have a different time dimension. For example, the Drought Code input into

[19] For example, the Buildup Index, which forms part of the fire behaviour indices capturing heat release, is constructed of non-linear functions depending on whether today's Duff Moisture Code (denoted as P) is below are above $0.4 * $ today's Drought Code (denoted as D) as shown in Eq. (4) in Appendix A. Subsequently the Buildup Index is used to calculate an intermediate form of the FWI, namely the duff moisture function, $f(D)$, which is once again derived from a non-linear function. More specifically, the duff moisture function is calculated as $0.626 * \mathrm{BUI}^{0.809} + 2$ if the Buildup Index is smaller or equal to 80, and as $1000(25 + 108.64e^{-0.023*\mathrm{BUI}})$ if the Buildup Index is larger than 80 as shown in Eq. (5) in Appendix A.

the FWI has a 53-day time lag and thus differs temporally from the precipitation and temperature in the general climate controls employed. Furthermore, the precipitation amount is adjusted to slope effects of the landscape. The Duff Moisture Code and the Drought Code are also adjusted for the day-length of the month (e.g., to account for the dry rate and potential evapotranspiration from the soil following rainfall), and thus go beyond using pure meteorological inputs in their elaborated construction designed for capturing fire danger. Our identifying assumption is thus that the instrument isolates the specific meteorological aspects leading to a substantially higher wildfire occurrence probability for predominantly forested areas conditional on controlling for fire danger in other areas that are arguably much less flammable, as well as for general climatological conditions within each of these area types.

3.2. Instrument construction

The FWI variable for forested area implemented as the instrument is created as follows. For the intersection of each region and FWI gridcell we tabulate the share of the four reclassified land cover types. To this end, we use the latest CLC version, i.e., the FWI years 2010–2012 are matched with CLC 2006 and the FWI years 2013–2018 are matched with CLC 2012. Each NUTS 3 region is then spatially joined with all the FWI gridcells that intersect with the region under the condition that the overlapping area is predominantly forested (> 50%). Subsequently, the average daily value of all matching FWI gridcells for each region is calculated. Finally, the daily mean FWI value for June, July, and August is calculated for each region as wildfires are most common in the summer months.[20] In our sample, the average FWI value for predominantly forested areas in the summer months is approximately 16 (see Table 4), which is described as "Moderate Fire Danger" according to the EFFIS classification[21] based on Van Wagner and Pickett (1985).[22]

3.3. Econometric specification

We evaluate the potential impact of wildfires on two economic variables in first differences, namely on the growth of the employment rate $\Delta\log(\text{EMP})$ over $t-1$ to t defined as $\log(\text{employed/total pop})_{i,t} - \log(\text{employed/total pop})_{i,t-1}$, and on the GDP growth rate $\Delta\log(\text{GDP})$ over $t-1$ to t defined as $\log(\text{GDP/capita})_{i,t} - \log(\text{GDP/capita})_{i,t-1}$, where i represents a NUTS 3 region and $t = [2011, \dots, 2018]$.

We estimate the following fixed effects 2SLS linear panel model instrumenting the fire impact variables with the FWI for predominantly forested areas:

$$\text{IMPACT}_{i,t-1\to t} = \beta_1 \text{FWI forest}_{i,t-1} + \mathbf{OFWI}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{C}_{i,t-1}\boldsymbol{\delta}_1 + \pi_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

$$\Delta\text{ECON}_{i,t-1\to t} = \beta_2 \widehat{\text{IMPACT}}_{i,t-1} + \mathbf{OFWI}_{i,t-1}\boldsymbol{\gamma}_2 + \mathbf{C}_{i,t-1}\boldsymbol{\delta}_2 + \pi_t + \mu_i + \varepsilon_{i,t}, \tag{2}$$

where $\text{IMPACT}_{i,t-1\to t}$ is a placeholder for the wildfire impact proxy variables, fire numbers or BA, $\text{FWI forest}_{i,t-1}$ is the daily mean Fire Weather Index in the summer months for predominantly forested areas, $\mathbf{OFWI}_{i,t-1}$ is a vector of the FWI for the other areas i.e., predominantly urban areas, rural areas, as well as for wetlands and water bodies in the summer months. Thereby, the FWI for the other land cover types are constructed similarly to the FWI for predominantly forested areas explained in Section 3.2. Moreover, $\mathbf{C}_{i,t-1}$ represents a vector of climatological controls including average summer and annual temperatures, precipitation, relative humidity, and wind speed. All the climatic controls are also implemented for each of the four land cover types separately and are created similarly to the land cover specific FWI variables explained in Section 3.2. π_t and μ_i account for unobserved year and regional fixed effects, respectively, and $\epsilon_{i,t}$ are idiosyncratic errors. $\Delta\text{ECON}_{i,t-1\to t}$ is alternatively defined by either $\Delta\log(\text{EMP})_{i,t-1\to t}$ or $\Delta\log(\text{GDP})_{i,t-1\to t}$, and $\widehat{\text{IMPACT}}_{i,t-1}$ is the predicted value of the wildfire impact variables in Eq. (1).

As our unit of analysis is at the regional level, one may worry about spatial correlation across regions. More specifically, the degree of economic integration between regions is likely to increase with geographical proximity and thus economic shocks may be spatially correlated. Hence we estimate our regression models with heteroskedasticity and autocorrelation consistent (HAC) standard errors that are robust to spatial correlation.[23] The necessary geospatial inputs for the estimation of spatial HAC standard errors are created using the longitude and latitude of the region's centroids. We choose a distance threshold for spatial correlation that corresponds to the radius of the NUTS 3 region's median area presuming a circular form of a unit, and add approximately 10% to this value which results in 33 km, in order to ensure that we include adjacent regions in the spatial correlation matrix.

We also explore whether there is a lagged impact of wildfires on regional economic outcomes by including up to $t-1-z$ lagged values of the IMPACT variable in Eq. (2). Note that in terms of instrumenting for these lagged values we do not use the complete set of lagged FWI variables in a joint 2SLS estimation framework because it would not be appropriate to expect $t-1-z$ values of FWI to be predictors for $t-1-z+n, n = 1, ..N$ values of IMPACT. Instead we estimate Eq. (1), generate the predicted values $\widehat{\text{IMPACT}}_{i,t-1}$, and include these and lagged values thereof in Eq. (2). However, as the contemporary and lagged values of the predicted $\widehat{\text{IMPACT}}_{i,t-1}$

[20] https://climate.copernicus.eu/esotc/2020/wildfires (accessed in December 2021).

[21] https://gwis.jrc.ec.europa.eu/about-gwis/technical-background/fire-danger-forecast (accessed in August 2021).

[22] See Table B2 in Appendix B for the complete classification of the FWI ranges.

[23] To test spatial correlation, we use Moran's I introduced by Moran (1950) and proposed by Cliff and Ord (1972). We implement a row-standardised inverse distance weight matrix. The null hypothesis of uncorrelated residuals is rejected for all combinations for both dependent variables and years. Hence, we implement spatial HAC standard errors.

Table 5
Wildfires and employment growth (2011–2018).

	Δlog(EMP)		FIRE	BA	Δlog(EMP)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FIRE $\times 10^{-2}$	−0.005 (0.005)					0.044 (0.055)	
BA		0.040 (0.046)					0.240 (0.307)
FWI forest			0.370*** (0.107)	0.067* (0.027)	0.000 (0.000)		
Climate Ctrl	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FWI Ctrl	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.30	0.30	0.60	0.31	0.40	0.39	0.39
Model	OLS	OLS	1st stage	1st stage	Reduced	IV	IV

Notes: (i) * p <0.05, ** p <0.01, *** p <0.001; (ii) spatial HAC standard errors in parentheses as implemented by Foreman (2020) with a distance cutoff value of 33 km; (iii) N = 1864; (iv) the first stage F-statistics of 37 and 23 for fire numbers (Column (3)), and burned area (Column (4)), respectively, indicate that a weak instrument problem can be excluded (Stock et al., 2002); (v) Δlog(EMP) denotes the growth of the employment rate; FIRE is the annual number of fires (stated in 100 fires); BA is the proportion of the annual burned area per region; FWI forest denotes the mean of the daily Fire Weather Index in the summer months for predominantly forested areas; (vi) FWI controls include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; climate controls include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; fixed effects include regional and time fixed effects.

will have their own distribution, using spatial HAC standard errors would no longer be appropriate. Were spatial correlation not an issue one could instead simply generate bootstrapped standard errors. Unfortunately, there is of date no accepted method to incorporate spatial correlation into standard bootstrapping procedures. We did experiment with 1000 re-sampled data sets using 2, 3, and 10-fold cross validation which preserved the spatial error structure. Yet, this resulted in unreasonably small standard errors, as upholding the spatial structure led to limited variation among the data sets.[24] Our solution is thus instead to implement HAC bootstrapped standard errors (1000 replications) in the lagged estimations without being able to take account of spatial correlation. Therefore, the lagged impact findings should be interpreted cautiously.

4. Results and discussion

4.1. Contemporary impact

In the first two columns of Table 5 we present the non-instrumented impact of our two wildfire proxies on employment growth, i.e., Eq. (2) but with direct measures of IMPACT rather than their instrumented counterparts. The results suggest there has been no significant impact of wildfires on aggregate employment growth during our sample period.

Columns (3) and (4) indicate that the estimations of Eq. (1) yield a strong first stage showing that the FWI for predominantly forested areas is a positive and statistically significant determinant of the wildfire impact variables at the 0.1 percent level for fire numbers and at the 5 percent level for BA. The positive effect meets a priori expectations since a higher fire danger index value arguably leads to more favourable conditions for both the outbreak and spread of wildfires. The effect size indicates an average increase of 0.4 fires per unit increase of the FWI (Table 5 Column (3)). An F-statistic of 37 for fire numbers indicates that a weak instrument problem can be excluded (Stock et al., 2002). Moreover, a unit increase of the FWI is associated with an increased share of BA of 0.007 percentage points (Table 5 Column (4)). The F test of joint significance in the first stage is 23 for BA, also indicating no weak instrument problem. Furthermore, the reduced form estimates displayed in Column (5) does not suggest an effect of the FWI for predominantly forested area on employment growth (Table 5).

The results of the IV estimations stated in Eq. (2) show a positive insignificant effect of the wildfire impact proxy variables on the growth of the employment rate. Thus, like previous research conducted in the US by Nielsen-Pincus et al. (2013) who report a general positive effect of large wildfires on employment growth of approximately 1% during the quarter of the fire at the regional (county) level, we find a positive effect for Southern Europe. However, it is not significant possibly because our study differs in that (i) we look at annual vs. their quarterly data, and thus a potential seasonal effect would not be detected, (ii) we include all fires, and therefore evaluate an aggregate effect, while Nielsen-Pincus et al. (2013) evaluate only large wildfire events,[25] and (iii) wildfires are on average much larger in the US than in Europe, and the resulting effect might thus be different.

Table 6 shows the effect of the wildfire proxy variables on GDP growth. The OLS results displayed in Columns (1) and (2) show a negative insignificant impact of wildfires on this economic activity indicator.[26] Unlike for aggregate employment, we find

[24] The standard errors for the 2-fold cross validation are about one quarter of the spatial HAC standard errors of the contemporary time period estimations.
[25] Thereby, a wildfire is defined as large when suppression spending exceeds one million US$.
[26] Columns (3) and (4) which show the first stage are identical to Table 5 and are reported for completeness.

Table 6
Wildfires and GDP growth (2011–2018).

	Δlog(GDP)		FIRE	BA	Δlog(GDP)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FIRE $\times 10^{-2}$	−0.005					−0.259*	
	(0.006)					(0.107)	
BA		−0.001					−1.425*
		(0.036)					(0.687)
FWI forest			0.370***	0.067*	−0.001***		
			(0.107)	(0.027)	(0.000)		
Climate Ctrl	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FWI Ctrl	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.45	0.60	0.31	0.54	0.38	0.28
Model	OLS	OLS	1st stage	1st stage	Reduced	IV	IV

Notes: (i) * p <0.05, ** p <0.01, *** p <0.001; (ii) spatial HAC standard errors in parentheses as implemented by Foreman (2020) with a distance cutoff value of 33 km; (iii) N = 1864; (iv) the first stage F-statistics of 37 and 23 for fire numbers (Column (3)), and BA (Column (4)), respectively, indicate that a weak instrument problem can be excluded (Stock et al., 2002); (v) Δlog(EMP) denotes the growth of the employment rate; FIRE is the annual number of fires (stated in 100 fires); BA is the proportion of the annual burned area per region; FWI forest denotes the mean of the daily Fire Weather Index in the summer months for predominantly forested areas; (vi) FWI controls include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; climate controls include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; fixed effects include regional and time fixed effects.

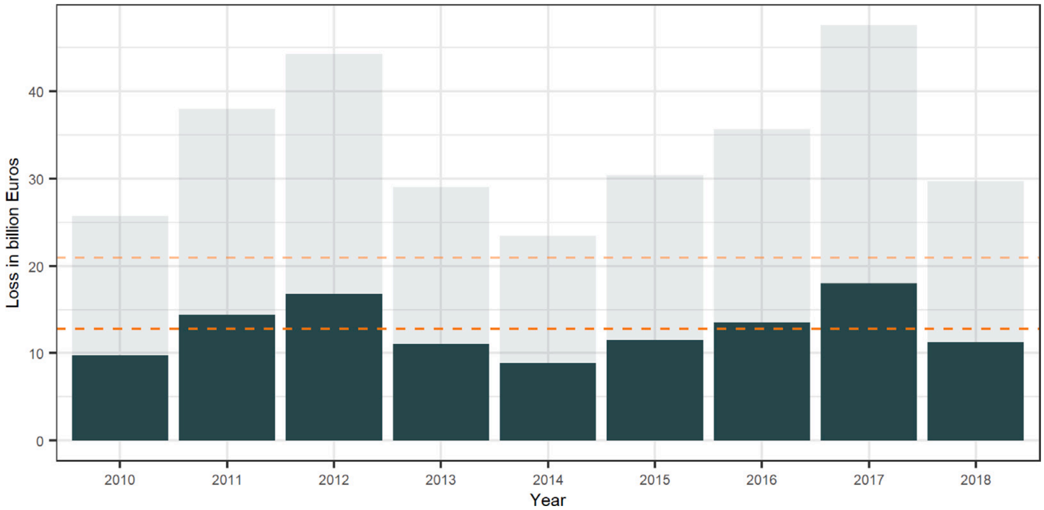


Fig. 4. Annual loss estimates based on a decrease in GDP growth for Southern Europe in billion euros (2010–2018).
Notes: (i) the solid bars indicate the lower bound and the transparent bars the upper bound of the estimate; (ii) the orange lines indicate the annual average losses (lower and upper bound) for the entire time period with an average of 102 wildfire affected regions per fire season.

a negative significant effect of the FWI for predominantly forested areas at the 0.1 percent significance level in the reduced form (Table 6 Column (5)). Both wildfire impact variables show a significant negative impact on GDP growth in the IV estimations (Columns (6) and (7)). One should note that the short-term negative GDP growth effects for wildfire affected regions found here are in line with the majority of the general natural disaster studies discussed in the introduction.

The point estimates on IMPACT of the IV specification in Table 6 indicate that, on average, an additional fire leads to a decrease in the regional annual GDP growth rate of 0.026% (Column (6)). As shown in Table 4, the mean wildfire number of the affected observations is 7 and thus the average wildfire affected region experiences a yearly decrease in the GDP growth rate of 0.18% ($-0.00259 * 7 = -0.018$). The largest number of annual wildfire events in a region observed is 129. Therefore, for the most severely hit region in the "worst" observed year over our sample period this would lead to a decrease of the annual GDP growth rate of 3.3% ($-0.00259 * 129 = -0.33$). The wildfire proxy variable BA (Column (7)) is also positive and significant and suggests a decrease in a region's yearly GDP growth rate, on average, of 0.11% ($-1.425 * 0.0077 = -0.011$) conditional on having experienced at least one wildfire. Table 4 shows that for the most heavily affected region in the data set, the aggregated annual BA was 33.82%. In such an extreme year, the regional GDP growth rate is predicted to decrease by 4.8% ($-1.425 * 0.3382 = -0.48$).

To get a better understanding of what these changes in growth rates mean in monetary values we calculate annual average losses for Southern Europe. To this end we multiply our estimated GDP growth effects with the mean GDP/capita value of 21,184 euros

Table 7
Wildfires and employment growth for NACE activity categories A, BE, and F (2011–2018).

	Δ log(EMP^{A})		Δ log(EMP$^{B\text{-}E}$)		Δ log(EMP^{F})	
	(1)	(2)	(3)	(4)	(5)	(6)
FIRE $\times 10^{-2}$	0.069		0.050		0.002	
	(0.158)		(0.074)		(0.228)	
BA		0.380		0.273		0.010
		(0.866)		(0.422)		(1.257)
FWI Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1,856	1,856	1,864	1,864	1,864	1,864

Notes: (i) * $p < 0.05$; (ii) spatial HAC standard errors in parentheses as implemented by Foreman (2020) with a distance cutoff value of 33 km; (iii) Δlog(EMP) denotes the growth in the employment rate; (iv) the superscript refers to the NACE activity where A includes agriculture, forestry and fishing, B-E is industry except construction, and F indicates construction; FIRE indicates the annual number of fires (stated in 100 fires); BA is the proportion of the annual burned area per region; (v) FWI controls include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; climate controls include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; fixed effects include regional and time fixed effects.

(as shown in Table 3) which implies an average loss of production of 23.3–38.1 euros/capita ($21,184 * 0.0011 = 23.3$ using BA and $21,184 * 0.0018 = 38.1$ using fire numbers). Subsequently, we multiply the average GDP/capita losses with the mean regional population of 538,000 to calculate the average loss in production for one affected region, which is 12.5–20.5 million euros. Fig. 4 shows the monetary losses due to lost production for each year derived by the multiplication of the per region estimate with the number of wildfire affected regions, and therefore shows the variation related to the severity and intensity of the fire seasons. The average number of affected regions from 2010 to 2018 is 102, which suggests that losses are in the region of 12.8–20.9 billion euros for Southern Europe in a given year.

4.2. Employment growth by economic activities

We next scrutinise the aggregate positive insignificant effect of wildfires on the growth of the employment rate in different economic activity categories to explore potential heterogeneous effects. To this end, the NACE economic activity sections are combined into six main categories as shown in Table 2.[27] The effects of categories A, B–E, and F are shown in Table 7, and the results of categories G–J, K–N, O–U are given in Table 8. Furthermore, the heterogeneous effects of wildfires on the growth of the employment rate by economic activity categories are visualised in Fig. 5, showing the point estimates and the 95% confidence intervals for each category. The impact of wildfires on the growth of the employment rate in agriculture, forestry and fishing (Table 7 Columns (1) and (2)), on industries other than construction (category B–E) (Table 7 Columns (3) and (4)), as well as on construction (Table 7 Columns (5) and (6)) is positive but insignificant. Furthermore, the results show an insignificant negative effect on sector O–U, that is public administration and defence, compulsory social security, education, human health and social work activities, arts, entertainment and recreation, and repair of household goods and other services (Table 8 Columns (5) and (6)).

We find that two employment categories are significantly affected by wildfires. First, there is a negative effect of wildfires on the employment growth rate in sector G–J, which includes wholesale and retail trade, transport, accommodation and food service activities, information and communication (Table 8 Columns (1) and (2)). This could indicate that employment activities related to retail and tourism (e.g., wholesale and retail trade; land, air, and water passenger transport; hotels, campgrounds, restaurants) are negatively affected. Once again, we multiply our estimates with the average fire numbers and BA which leads to a regional annual decrease in the rate of employment growth in category G–J of 0.09–0.15% ($-0.00213 * 7 = -0.015$ using fire numbers (Column (1)) and $-1.174 * 0.0077 = -0.009$ using BA (Column (2))) for wildfire affected regions.

We quantify the estimated results of wildfires on employment growth for the specific activity categories in terms of job numbers to enhance the understanding of this magnitude. On average, 62,519 people (28.8% of the working population) are employed in the retail and tourism sections G–J per region as shown in Table B3 in Appendix B. Our estimates translate into 56–94 jobs lost per affected region annually ($62,519 * 0.0009 = 56$ using BA and $62,519 * 0.0015 = 94$ using fire numbers). With 102 regions that experience a wildfire in an average year this leads to a loss of 5,712–9,588 jobs for Southern Europe in the employment activity sectors including retail, transportation, as well as accommodation and food service activities.

Our findings concur with previous studies looking at recreational activities and tourism related to wildfires. For example, Kim and Jakus (2019) evaluate tourist flows in response to wildfires studying national park visits in Utah. The authors find a decrease in tourism in four out of five national parks and suggest an annual loss of 31–53 jobs based on the estimated loss in labour income. Furthermore, Gellman et al. (2022) study the effect of wildfires and smoke exposure on more than 1000 campgrounds in the western US showing that 1 million visitors per year are affected and estimate a decline in campground use. Evidence of wildfires affecting tourism-related industries in Southern Europe is provided by Molina et al. (2019) who estimate the economic susceptibility of

[27] One should note that there is no information for category A for 1 region.

Table 8
Wildfires and employment growth for NACE activity categories G–J, K–N, and O–U (2011–2018).

	Δ log(EMP$^{G\text{-}J}$)		Δ log(EMP$^{K\text{-}N}$)		Δ log(EMP$^{O\text{-}U}$)	
	(1)	(2)	(3)	(4)	(5)	(6)
FIRE $\times 10^{-2}$	−0.213*		0.308*		−0.107	
	(0.089)		(0.138)		(0.066)	
BA		−1.174*		1.695*		−0.591
		(0.519)		(0.817)		(0.417)
FWI Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1,864	1,864	1,864	1,864	1,864	1,864

Notes: (i) * p <0.05; (ii) spatial HAC standard errors in parentheses as implemented by Foreman (2020) with a distance cutoff value of 33 km; (iii) Δlog(EMP) denotes the growth in the employment rate; (iv) the superscript refers to the NACE activity where G–J includes wholesale and retail trade, transport, accommodation and food service activities, information and communication, K–N is contains financial and insurance activities, real estate activities, professional, scientific and technical activities, administrative and support service activities, and O–U includes public administration and defence, compulsory social security, education, human health and social work activities, arts, entertainment and recreation, and repair of household goods and other services; FIRE indicates the annual number of fires (stated in 100 fires); BA is the proportion of the annual burned area per region; (v) FWI controls include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; climate controls include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; fixed effects include regional and time fixed effects.

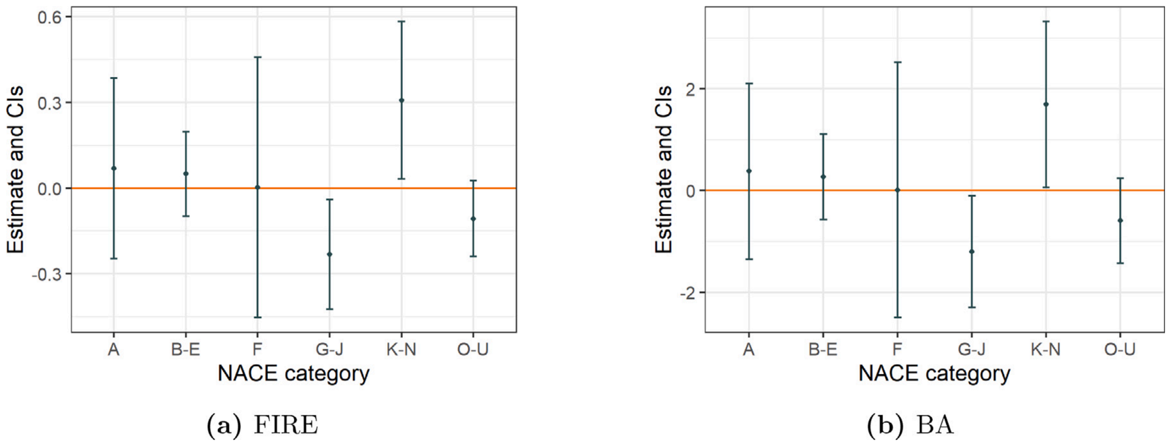


Fig. 5. Wildfires and employment growth by economic activity category (2011–2018).
Notes: (i) the economic activity categories are defined following the Statistical classification of economic activities in the European Community abbreviated as NACE (see Table 2 for the full NACE economic activities classification); (ii) FIRE indicates the annual number of wildfires per region; BA in % denotes the annual burned area relative to the total area per region; (iii) CIs = confidence intervals.

recreation activities due to wildfires for the "Aracena *y* Picos de Aroche Natural Park" in Spain and show a susceptibility increase of 58 million euros due to travel and incidental costs. Moreover, Otrachshenko and Nunes (2022) estimate the effect of forest fires on tourist arrivals for 278 municipalities in Portugal and show that a 1% increase in BA in a given year reduces the tourist arrivals in that year by 3.5%.

The second significantly affected category, is the employment growth in NACE activity sections K–N, which include financial and insurance activities (e.g., risk and damage evaluation, financial leasing, reinsurance), real estate activities, professional, scientific and technical activities (e.g., legal and accounting services, architectural and engineering activities) as well as administrative and support service activities (e.g., renting and leasing of motor vehicles and construction machinery, temporary employment agencies activities, security and investigation activities, services to buildings and landscape activities). The magnitude of the effects indicate that wildfires lead to an increase in the regional annual employment growth in these sectors of 0.13–0.22% ($0.00308 * 7 = 0.022$) using fire numbers (Column (3)) and $1.695 * 0.0077 = 0.013$ using BA (Column (4)) conditional on a region having experienced at least one wildfire. The estimated positive employment effect in this NACE category seems sensible in response to wildfires, particularly as it incorporates insurance and damage evaluation, real estate activities, temporary employment activities (i.e., this includes short-term contracting possibly in the labour intensive construction sector or for additional firefighters), as well as services to buildings and landscapes activities which comprises cleaning of affected buildings and landscapes in the aftermaths of a wildfire.

On average 32,137 people (11.1%) work in sections K–N (see Table B3 in Appendix B) and thus a wildfire affected region experiences an annual increase of 42–71 jobs in this sector ($32,137 * 0.0013 = 42$ using BA and $32,137 * 0.0022 = 71$ using fire

Table 9
Wildfires and employment and GDP growth with lags (2011–2018).

	Δlog(EMP)			Δlog(GDP)		
	(1)	(2)	(3)	(4)	(5)	(6)
$FIRE_t \times 10^{-2}$	0.044	0.041	0.013	−0.259**	−0.259**	−0.222**
	(0.064)	(0.069)	(0.061)	(0.085)	(0.088)	(0.084)
$FIRE_{t-1} \times 10^{-2}$		0.089**	0.065		−0.009	−0.009
		(0.034)	(0.036)		(0.044)	(0.037)
$FIRE_{t-2} \times 10^{-2}$			0.057			−0.004
			(0.037)			(0.040)
BA_t	0.240	0.135	−0.040	−1.425**	−1.435**	−1.241**
	(0.354)	(0.382)	(0.347)	(0.468)	(0.477)	(0.444)
BA_{t-1}		0.524**	0.543**		0.052	0.171
		(0.193)	(0.207)		(0.260)	(0.210)
BA_{t-2}			0.208			0.130
			(0.208)			(0.191)

Notes: (i) * p <0.05, ** p <0.01; (ii) standard errors in parentheses are bootstrapped (1000 replications) and clustered on the regional level; (iii) N = 1864; (d) Δlog(EMP) denotes the growth in the employment rate and Δlog(GDP) is the GDP growth rate; $FIRE_t$ indicates the number of fires in year t (stated in 100 fires); BA_t is the proportion of the annual burned area per region in year t; (iv) all estimations are run with FWI controls that include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; climate controls that include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; as well as fixed effects including regional and time fixed effects.

numbers). For an average fire season (i.e., 102 wildfire affected regions), this leads to an additional 4,284–7,242 jobs related to financial, insurance, real estate, as well as administrative and support service activities in Southern Europe.

4.3. Lagged impact

Wildfires might have a more sustained effect on regional economies. Therefore, we explore whether there are lagged effects on regional employment and GDP growth of wildfires by including two lags of the wildfire impact variables in Eq. (2). As noted earlier, the reported standard errors of all lagged estimations are not robust to spatial correlation, and thus must be interpreted relatively cautiously.

The results shown in Table 9 suggest consistently that it is only in the contemporary year that the GDP growth rate (Columns 4–6) is affected for both wildfire impact variables. In contrast, the results regarding the effect of BA on aggregate employment growth (and fire numbers for lag 1) indicate that there is a positive effect of the prior year. This would imply, subject to the concerns regarding the lack of spatial correlation taken account of in the standard errors, that a region's annual aggregate employment growth increases on average by 0.04–0.06% ($0.00089 * 7 = 0.006$ using fire numbers in Column (2), $0.524 * 0.0077 = 0.004$ using BA in Column (2), or $0.543 * 0.0077 = 0.004$ using BA in Column (3)) conditional on having experienced at least one wildfire. This aligns with recent research on the economic effects of natural disasters presented in Deryugina (2022) showing long-term labour market resilience for wealthy countries.

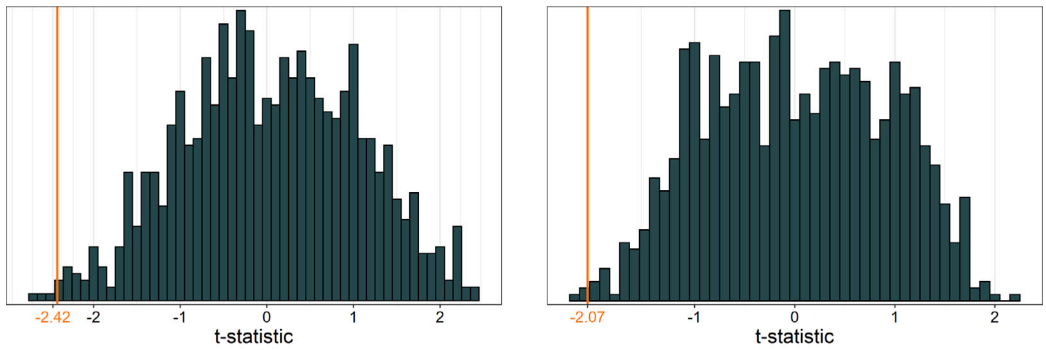
4.4. Robustness checks

To test the robustness of our baseline estimations, we conduct the Fisher randomisation test introduced by Fisher (1937) for the estimates of the wildfire impact variables on GDP growth. We randomly reshuffle the fire numbers and BA across space and time (keeping the instrument and the control variables fixed) and run the IV regressions performing 1000 iterations. The results displayed in Fig. 6 show the high level of significance of our results (indicated by the t-statistic of the actual estimate) with a p-value of 0.004 for both fire numbers and for BA. This demonstrates that our results are not driven by chance.

As described in Section 3, we choose 33 km as the distance cutoff for the spatially robust HAC standard errors since this reflected the median distance between regions' centroids. To explore how sensitive our results are to this choice we incrementally increase the threshold and re-estimate Eq. (2). Fig. 7 shows that the spatial standard errors increase in distance and become insignificant after we choose values of approximately 40 to 140 kilometres for the BA and fire numbers, respectively. Thus, our findings are only robust to assuming that potential regional economic shocks or spillover effects are limited to mostly adjacent regions.

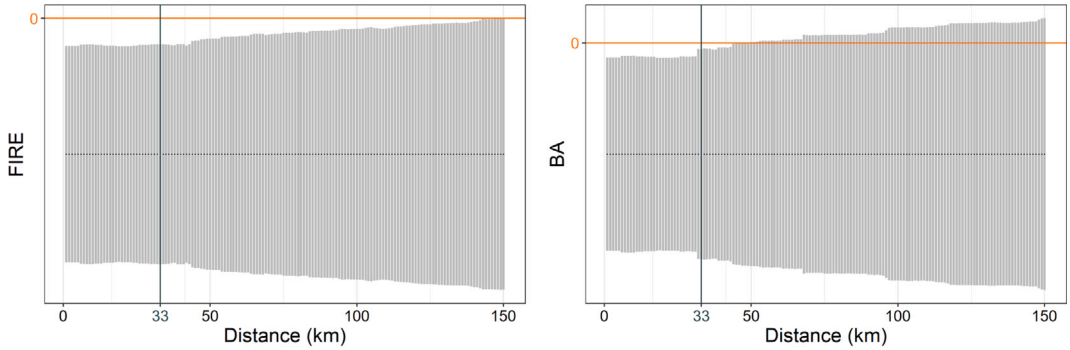
To explore a potential economic impact beyond the directly affected BA we create buffers of one and five kilometres around each wildfire BA polygon. The underlying idea is to evaluate whether the effects extend to surrounding areas given those arguably suffer from indirect impacts (e.g., road closures, business downtime, decrease in tourism). Similar to the baseline estimations, we find significant negative effects of the wildfire impact variables on the GDP growth rate and insignificant positive effects on employment growth for the buffered estimations. The magnitude of the coefficient decreases with increasing buffer size as shown in Table 10.

Finally, one might be concerned that migration potentially impacts our findings. As explained in Section 3 we implement spatial standard errors, robust to various cutoffs between 40 to 140 kilometres, in our main estimations. This would take account of migration into neighbouring regions as long as these act through shocks captured in the error term. We additionally run our



(a) FIRE (b) BA

Fig. 6. Fisher randomisation test of wildfire impact variables and GDP growth with 1000 iterations.
Notes: (i) the vertical line indicates the t-statistic of our actual estimate; (ii) FIRE indicates the annual number of wildfires per region; BA in % denotes the annual burned area relative to the total area per region.



(a) FIRE (b) BA

Fig. 7. Spatial HAC standard errors with varying distance cutoff estimating the wildfire impact on GDP growth.
Notes: (i) the vertical line indicates the selected cutoff value of 33 km; (ii) FIRE indicates the annual number of wildfires per region; BA in % denotes the annual burned area relative to the total area per region.

Table 10
Wildfires and employment and GDP growth with buffered estimations (2011–2018).

	Direct	Buffer 1 km	Buffer 5 km
Δlog(EMP)			
FIRE $\times 10^{-2}$	0.044	0.016	0.001
BA	0.240	0.088	0.012
Δlog(GDP)			
FIRE $\times 10^{-2}$	−0.259*	−0.093*	−0.007*
BA	−1.425*	−0.522*	−0.070*

Notes: (i) * p <0.05; (ii) direct effects incorporate the actual burned area; for potential effects beyond the burned area, buffers of size 1 and 5 km area created around each polygon; (iii) Δlog(EMP) denotes the growth of the employment rate; Δlog(GDP) is the per capita GDP growth rate; FIRE is annual number of fires per region (in 100 fires); BA is the proportion of the annual burned area per region; (iv) climate controls include summer and annual means of the variables temperature, precipitation, relative humidity, and wind speed for each of the four land cover type categories separately; FWI controls include the Fire Weather Index for predominantly urban and agricultural areas as well as for wetlands and water bodies; fixed effects include regional and time fixed effects.

specification in Eq. (2) but using regional population growth as the dependent variable. More precisely, as long as births and deaths are not directly affected by wildfires, or their effects cancel each other out, or in net are less than any effect on migration, then any impact on population growth can be considered to be due to net migration. However, the results of this exercise showed that neither the reduced form (coefficient 0.00; standard error 0.00) nor the IV estimates for fire numbers (coefficient 0.007; standard error 0.008) and BA (coefficient 0.039; standard error 0.045) were significant. Thus, either there is no effect on net migration or the effect is cancelled out by impacts of the birth net of the death rate.

Nevertheless, we need to emphasise that our study estimates the aggregated effects of all wildfire occurrences per region and year, most of which are arguably not disastrous. This is in strong contrast to the existing migration literature in the natural hazards context that sets a focus on large-scale devastating events (Karácsonyi et al., 2021).[28] For example, Sheldon and Zhan (2022) find county out-migration following hurricanes and floods using Federal Emergency Management Agency (FEMA) data. Regarding wildfires, Winkler and Rouleau (2021) suggest that extreme wildfires (as declared by FEMA) in the US may be associated with out-migration. Similarly, Boustan et al. (2020) report increased out-migration for severe fire events using FEMA data from 1920 to 2010 in the US, although it needs to be pointed out that in their specification a severe fire event is associated with at least 25 moralities. Out of the more than 6000 wildfires in our dataset, less than a hand full would be categorised accordingly.

There are reasons why residents are unlikely to migrate after being affected by a wildfire. For instance, areas that are fire-prone often simultaneously draw people due to their intrinsic environmental amenities, as extensively outlined in McConnell et al. (2021). More precisely, even for large and devastating wildfires, the negative impact may not be big enough to outweigh the amenity-draw to that very place. Evidence in line with this notion shows that even for disastrous wildfire events, such as the California's 2017 North Bay fires which resulted in more than 6000 structures damaged or destroyed, a small minority of affected households moved out of the county (Sharygin, 2021). Finally, a recent study by McConnell et al. (2021) investigates fires that are known to have destroyed at least one building, i.e., 16% of fires in their sample, and find in-as well as out-migration for the entire sample and an increase in out-migration for fires that destroyed more than 17 buildings. The authors state as a broader conclusion that residents largely remain in fire-prone regions after less destructive events, which per definition are arguably more destructive than the majority of fires in our data set.

5. Conclusions

In this paper we link high resolution satellite data of aggregate wildfire burned areas with regional economic data for Southern Europe, enabling us to contribute to a deeper understanding of how these events impact local economic outcomes. Given that wildfire incidents are likely correlated with various unobservable factors, such as land management policies, wildfire prevention strategies, and land-use changes, and can be set intentionally, the events are treated as endogenous in our analysis. To overcome this concern we use a measure of wildfire occurrence probability for predominantly forested areas based on relevant climatic features as an instrumental variable, while controlling for fire danger in non-forested area as well as for general climatic conditions that might directly affect regional economies. Importantly, the analysis indicates that not taking account of the endogeneity of wildfires is likely to lead to biased estimates on economic impacts. The proposed instrumental variable strategy might thus also prove to be a useful approach for other researchers interested in the economic implications of wildfires.

Our causally identified results for Southern Europe show a consistent negative contemporary effect of wildfires on the annual regional GDP growth rate ranging from 0.11 to 0.18%. For the most severe wildfire years, the effect can lead to a decrease in the GDP growth rate of approximately 3.3–4.8% using fire numbers and burned area, respectively. The disaggregated employment analysis by economic activity categories reveals heterogeneous impacts, where industries such as wholesale and retail trade, transport, accommodation and food service activities are experiencing a negative employment effect of 0.09–0.15%, plausibly as a result of disruptions related to tourism. In contrast, our results show a positive effect of wildfires on regional employment growth of 0.13–0.22% in sectors including financial, insurance, and real estate activities, as well as short-term contracting activities.

Overall our study provides novel evidence that wildfires lead to a significant decrease in the regional GDP growth rate for Southern Europe. Although wildfires have formed an integral part of the Mediterranean landscapes for centuries, the public institutional response could benefit from an extensive evaluation of mitigation and prevention mechanisms (e.g., mechanical clearing, prescribed burning, grazing, land management activities) to reduce the negative impacts on local economies. As illustrated in Bayham et al. (2022), economic interdependencies and inefficiencies in fire-prone landscapes render wildfire management highly complex and large research gaps remain. European wide data collection efforts on these aspects at the regional level would allow researchers to further investigate the possible role of these interventionist factors. Such insights would importantly allow regional policy makers to explicitly evaluate strategies to strengthen the resilience of regional economies, particularly since the potential damage of wildfires is predicted to become more pronounced in the future (Dupuy et al., 2020).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[28] We hereby focus on studies looking at revealed preferences and do not discuss publications studying stated preferences (e.g., surveys quantifying the intention to move after severe wildfire events) such as Nawrotzki et al. (2014) or Berlin Rubin and Wong-Parodi (2022).

Appendix A. Fire weather index equations

Given the complexity of the FWI calculations, we limit ourselves to illustrate the derivations of the direct fire behaviour inputs to the FWI, which are the Initial Spread Index (ISI) and the Buildup Index (BUI). Thus, we will not elude to the underlying functions of the respective inputs, namely the function of wind $f(W)$, the fine fuel moisture function $f(F)$, today's Duff Moisture Code denoted as P, and today's Drought Code denoted as D. The exposition of the exact equations here forth strongly draws on Van Wagner and Pickett (1985), where the full set of equations based on the primary input variables is described.

The Initial Spread Index is defined by Eq. (3), whereby $f(W)$ is a function of wind and $f(F)$ is the fine fuel moisture function.

$$\text{ISI} = 0.208 * f(W) * f(F) \tag{3}$$

The Buildup Index shown in Eq. (4) is a function of today's Duff Moisture Code (DMC) denoted as P and today's Drought Code (DC) denoted as D.

$$\text{BUI} = \begin{cases} 0.8 * PD/(P + 0.4 * D), & \text{if } P \leq 0.4 * D \\ \text{P} - [1 - 0.8 * D/(P + 0.4 * D)][0.92 + (0.0114 * P)^{1.7}], & \text{if } P > 0.4 * D \end{cases} \tag{4}$$

The output of Eq. (4) is subsequently used as input to calculate the duff moisture function, $f(D)$, shown in Eq. (5).

$$f(D) = \begin{cases} 0.626 * \text{BUI}^{0.809} + 2, & \text{if BUI} \leq 80 \\ 1000(25 + 108.64e^{-0.023*\text{BUI}}), & \text{if BUI} > 80 \end{cases} \tag{5}$$

Eq. (6) derives B, which is an intermediate form of the FWI, by scaling and multiplying today's ISI with the duff moisture function.

$$B = 0.1 * \text{ISI} * f(D) \tag{6}$$

Finally, Eq. (7) shows the derivation of the FWI in its final form.

$$\text{FWI} = \begin{cases} B, & \text{if B} \leq 1 \\ 2.72(0.434 * ln(B))^{0.647}, & \text{if } B > 1 \end{cases} \tag{7}$$

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2023.102787.

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